Enhanced Curvlet Transform based Artificial Neural Network for Brain Tumor Diagnosis

M. Venkata Ramana, E. Sreenivasa Reddy, CH. Satayanarayana

Abstract— ***Brain tumor is one of the health problems faced by human beings. It often leads to death of people. Detecting it early can help in taking treatment and improve quality of life. The detection has to be made with MRI brain tumor images. Fourier transform, wavelet transform, Ridgelet transform and Curvelet transform are the techniques exist for representing images. Fourier transform can represent signals with only frequency domain and information on temporal domain is missing. To overcome this drawback, wavelet transform is used which can represent signal using wavelets in both time and frequency domains. However, wavelets are not good for images with different angles and different scales. Ridgelets could handle images with line singularities but could not handle images with curves. Curvlet transform can overcome this problem besides representing images with different scales and different angles. Curvlet Transform (CT) with enhancements can support dynamic texture classification for detection of brain tumor. Thus in this paper Enhanced CT (ECT) is used to have better diagnosis of brain tumor. A framework with underlying algorithms based on ECT is designed and implemented. A prototype application is built using MATLAB to demonstrate proof of the concept. The empirical results revealed that the proposed method has significant performance improvement over state of the art approaches.***

Index Terms – ***Curvlet transform, enhanced curvelet transform, brain tumor detection framework***

1. INTRODUCTION

Brain tumor is one of the major concerns and causes of death in the world. Uncontrolled growth of tissues in human brain causes brain tumor. It is a life-threatening disease. World Health Organization (WHO) classified brain and central nervous system tumors into 120 categories. Broadly they are divided into two types known as benign and malignant. Human brain is captured with Magnetic Resonance Imaging (MRI) technology [8]. Thus MRI images are widely used in the research of brain tumor detection. There are different grades in brain tumor based on the severity of disease. The four rows of brain images in Figure 1 show the grades. The first row images reflect grade I disease. The second row images show the grade II disease. Similarly third row shows grade III and fourth row indicates existence of grade IV tumor respectively.

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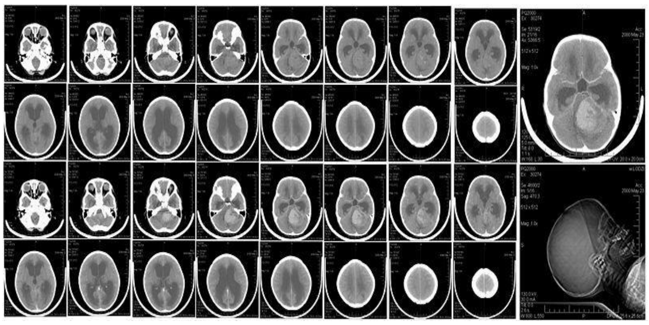

Figure 1: MRI images showing different grades of brain tumor

In the grade I, the tumor cells are growing slowly. However, they appear like normal or benign. When it moves to grade II, III and IV, it is understood that the severity of disease is increased and the level of malignancy is more. Malignant tumor is growing faster in grade IV. MRI technology is powerful in producing images of human organs. Visual interpretation of tumors in human brain with the help of MRI imagery is known to doctors. However, doing it manually is error-prone and it needs automated and computer-aided approaches. Towards this end many automated techniques came into existence.

Of late curvelet transform technology in image processing showed its utility in different applications. Curvelet transform can support non-adaptive representation of objects in images. Moreover, it is best used for images with different edges. Thus it became an ideal candidate for processing images to have accurate detection of tumors or any such objects. This technology is used for brain tumor detection as explored in [1], [5], [6], [16] and [19]. However, an effective framework that contributes more to the detection of brain tumor based on enhanced curvelet transform is still desired. To overcome this drawback, we proposed a framework known as Curvlet Transform and ANN based Brain Tumor Detection (CTANN-BTD). Our contributions are as follows.

- We proposed a framework known as CTANN-BTD which exploits curvelet transform and ANN techniques for diagnosis of brain tumor disease using MRI images.
- Algorithms are proposed to achieve feature extraction, feature selection and efficient classification leading to diagnosis of brain tumor with an automated approach.
- A prototype application is built using MATLAB for evaluating the proposed framework.

The remainder of the paper is structured as follows. Section 2 reviews literature on brain tumor detection techniques. Section 3 presents the proposed framework for brain tumor diagnosis. Section 4 presents experimental setup and evaluation methodology. Section 5 presents experimental results while section 6 concludes the paper and provides possibilities of future scope of the research.

2. RELATED WORK

This section provides review of literature on brain tumor detection methods and the utility of curvlet transform for the same. Pandian and Balasubramanian [1] explored different classifiers like ELM and DNN for image texture classification. They employed techniques like local ternary patterns, contourlet and curvlet. MRI images are used for brain tumor detection. Similar kind of work is found in [16]. Bhateja et al. [2] on the other hand investigated maximum selection rule and PCA in curvelet domain for medical image fusion. This method was intended for medical diagnosis. Salcedo-Sanz et al. [3] explored Support Vector Machines (SVM) for diagnosis of brain tumor. The combination of Curvlet Transform and SVM are used for classification of brain tumor images in [6] with texture features known as Grey Level Co-occurrence Matrix (GLCM). Curvlet transform is used for radar signal processing in [7]. Srinivas et al. [4] explored dictionary learning concept to retrieve medical images effectively. They defined an algorithm known as Orthogonal Matching Pursuit (OMP). IRMA is the dataset used.

Varsha and Shyry [5] employed Neural Netowrk (NN) for detecting brain tumor. Enhancement approaches in frequency and spatial domain and de-noising in wavelet domain are used in [8] for detecting tumor in MRI brain images. Fuzzy C Means (FCM) and NN are employed in [9] using Gray Level Run Length Matrix (GLRLM). On the other hand Sheela and Babu [10] used combination of Fractional PSO and Fuzzy Bisector based K-Means with MRI images. Different techniques like PCA, NN and DCT are used in [11] for diagnosis of brain tumor. Curvlet Transform (CT) and an enhanced FCM are used for segmentation of tumor in MRI images [12]. Different methods of detecting tumor are reviewed in [13], [18], [22] while combination of CT and Wavelet image fusion is employed in [14] along with NN. Curvelet domain with PCA is used for image fusion in [15]. Pradeep et al. [17] explored CT and MRI images for segmentation to detect tumors. Curvelet transform and ANN are used in [19] while a comparative study of different techniques is found in [20].

Genetic Algorithm (GA) with image fusion is employed in [21]. Curvelet transform and compressive sensing for noise removal is explored in [23]. Curvelet transform and relative assessment approaches are used in [25] for de-noising remote sensed imagery. 3D Discrete Transform is explored in [26] while curvelet representation of wave propagators is examined in [27]. Continuous curvelet transform is studied in [28]. Fast discrete curvelet transform [29], tight frames of curvelets [30], operators of curvelets and Fourier integral [31], multiscale transforms [32], recognition of dynamic textures with curvelet transform [33] are different approaches used to work with images. Different applications using curvlet transform is studied in [34]. Both curvelet and wavelet transforms are employed with fusion approach in [35] for brain tumor detection.

Classification of hyper spectral imaging (HSI) is done using curvelet transform in [36]. Contrast sensitivity is explored using wavelet and curvlet transform techniques in [37]. Noise suppression is made using curvlet transform in air borne magnetic data [38]. Fault diagnosis [39], fusion of multi-spectral and panchromatic images for high quality [40], fibronectin variants classification [41], object detection in video using curvlet transform [42] and PCA and curvelet transform for image fusion [43] are other utilities found in the literature on curvelet transform technique. From the review of literature it is understood that brain tumor detection is very active area of research. However, curvlet transform based solutions are less and an effective approach based curvlet transform is highly desired. It is the endeavour of this paper.

3. PROPOSED FRAMEWORK

We proposed a framework for effectively detecting brain tumor automatically. It is a computer aided approach in which different techniques are employed. MRI images are taken as dataset and it is subjected to pre-processing. In the pre-processing phase, the MRI images are divided into training and testing sets. The training set is a collection of brain images that are labelled. These images are used for training a classifier. Testing images are the brain images that are not yet classified and in other words, they are not labelled. The framework is known as Curvelet Transform based Artificial Neural Network for Brain Tumor Detection (CTANN-BTD). Figure 2 illustrates the functionalities involved in the framework.

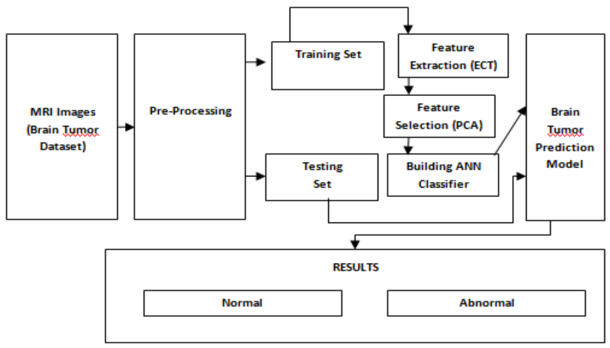

Figure 2: Overview of Curvelet Transform based ANN for Brain Tumor Detection (CTANN-BTD) framework

After pre-processing the training set is subjected to feature extraction. Feature extraction is very important to complete the research on ECT based ANN for classification. Enhanced Curvlet Transform described in Section 3.1 is used for feature extraction. Once features are extracted, it is essential to identify best features for improving accuracy of classification. It helps in finding the features that are highly relevant to the task in hand or the given objective. It is achieved by using PCA described in Section 3.2. After obtaining features, these features are given to ANN classifier described in Section 3.3 for training purpose. ANN classifier is learned and a knowledge model or brain tumor detection model is created. So far, this process is done offline. Once the detection model is ready, then online process of detection of brain tumor is carried out. It takes testing set as input and classifies it into normal and abnormal. Precisely, this is the functionality of the framework. More details are provided in the following sub sections.

3.1 EnhancedCurvelet Transform (ECT) for Feature Extraction

Enhanced curvlet transform is employed to obtain coefficients of brain tumor images. The coefficients form as descriptor for such images. In other words, ECT results in a novel descriptor of images. Curvlet coefficients obtained from image are represented as in Eq. 1.

$$C^D(j,l,k) = \sum D \frac{sm<M}{Dsn<N}, F[M.N]\varphi^D{}_{j,l,k}[m,n]$$

(1)

Where, $\varphi^D{}_{j,l,k}[m,n]$ is known as curvlet mother function.

Location parameters are denoted as *k*, orientation is represented by *l* and scale is denoted by *j*. The curvlet transform coefficients are computed as follows. Fourier samples are obtained from image using 2D FFT. Product of Fourier samples of image and digital curvelet of Fourier domain is made. Then wrapping of the product is made to have rectangular support. On the wrapped result, inverse 2 D FFT is applied. The result of ECT is to have curvlet coefficients at given scale and orientation. Curvelab toolbox is used to in order to complete the feature extraction process. Feature extraction algorithm is as follows.

Algorithm: ECT based Feature Extraction (ECT-FE)
Input: Brian images dataset D
Output: Feature Descriptor Vector FD

1. **For each** image img in D
2. Apply ECT on img
3. Compute curvelet coefficients for different scale and orientations
4. Add coefficients to FD
5. **End For**
6. Return FD

Algorithm 1: ECT based feature extraction

As given in Algorithm 1, the features of given brain images are extracted and returned as a vector of FD for all given images. ECT is used to obtain coefficients of images. Thus a feature descriptor is generated for each image. This descriptor is crucial for building a knowledge model in training phase and used later in testing phase

3.2 PCA for Feature Selection

The extracted curvelet coefficients or features for brain images are very high. There needs to be reduction in features for improving efficiency of classification. Otherwise, it leads to sub optimal performance. This is the significance of feature selection in the brain tumor detection methodology proposed in this paper. The features obtained in the feature extraction phase of the framework (Figure 2) are subjected to feature selection process. PCA is well established technique used for reducing number of features that are close to the problem in hand. PCA computes empirical mean using Eq. 2.

$$u[m] = \frac{1}{N}\sum_n^N = 1\, X[m,n] \quad (2)$$

Afterwards, the deviations from the mean are computed as in Eq. 3.

$$B[M \times N]: B = X - u,$$

(3)

Afterwards a co-variance matrix is built as in Eq. 4.

$$C: C = \frac{1}{N} B.B^*$$

(4)

For the computed co-variance matrix, eigenvectors and corresponding eigenvalues are found as in Eq. 5.

$$C, D[P,q] = \lambda_m\ for p = q = m$$

(5)

Then rearrangement of the eigenvalues of eigenvectors is made as in Eq. 6.

$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \dots . \geq \lambda_n$$

(6)

Then feature vector is formed and filtered to have features that have highest eigenvalues. This will result in the features selected for building classifier. Algorithm 2 provides concisely the way feature selection takes place using PCA technique.

Algorithm:ECT based Feature Selection (ECT-FS)
Input: Feature descriptor vector for all images FD
Output: Feature descriptor with selected features FD'

1. Using FD compute empirical mean (Eq. 2)
2. Compute deviations from the mean (Eq. 3)
3. Generate covariance matrix (Eq. 4)
4. Obtain eigenvectors with corresponding values (Eq. 5)
5. Rearrange eigenvectors
6. Add vectors with highest eigenvalues to FD'
7. Return FD'

Algorithm 2: ECT based feature selection

The feature descriptor vector produced by Algorithm 1 is used as input to the feature selection algorithm. Then the computation of empirical mean, deviations from mean, generation of covariance matrix, generating eigenvectors, rearranging them and finding only eigenvectors with highest eigenvalues are finally selected as features for training classifier.

3.3 ANN for Brain Tumor Diagnosis

Building ANN classifier is the final step in the training phase. The selected features FD' is used as input and it produces a knowledge model or brain tumor detection model. This model is used in the testing phase to label unlabelled brain tumor images. ANN is widely used mathematical model for solving complex problems such as OCR, medical image classification, object recognition and pattern recognition to mention few. A typical ANN with back propagation is presented in Figure 3.

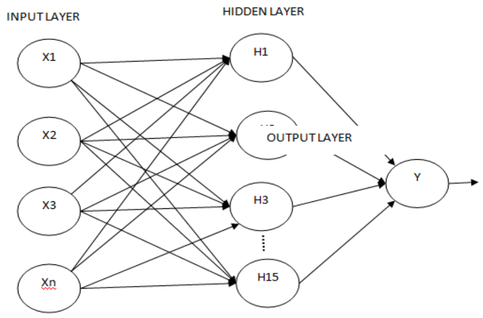

Figure 3: Artificial Neural Network with Back Propagation

The ANN has input hidden and output layers. A transfer function known as log sigmoid function is explored in hidden layer while linear transfer function is employed in output layer. The training given to the network using FD' obtained in the feature selection phase produces a knowledge model or brain tumor detection model. While training the ANN, MSE is used as error related objective function. Once training is carried out, the testing phase is achieved by using the following algorithm.

Algorithm: ECT based ANN classification (ECT-ANN)
Input: FD' (output of ECT-FS) based detection model, testing set T
Output: Labelling such as normal or abnormal

1. For each img in T
2. Apply ANN model
3. Label img
4. Add img to T'
5. End For
6. Return T'

Algorithm 3: ECT based ANN for classification

The algorithm takes the outcome of the ECT-FS and also the training brain tumor images. The back propagation based ANN works to classify the given input images. The knowledge model is used to predict class labels for images. The classification of test images is made into normal and abnormal indicating the absence or presence of brain tumor. Thus the proposed framework is used for brain tumor diagnosis.

4. EXPERIMENTAL SETUP

The environment used for experiments include a PC with Intel core i5 processor with 1.70GHz speed and 4 GB of main memory. MATLAB 9.4 (R2018a) is used for empirical study. Curvelab toolbox version 2.0 is used for extracting features from brain tumor images. A total of 160 MRI brain images are used for experiments. Out of them 20 normal and 140 abnormal images are there. In training set 112 abnormal images and 16 normal images are available. In testing set there are 28 abnormal images and 4 normal images. Figure 4 shows the dynamics of brain image dataset.

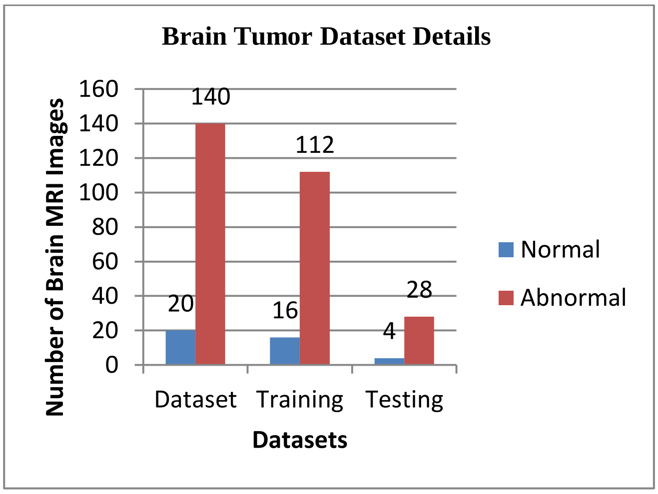

Figure 4: MRI brain image dataset details

After completion of the experiments, the proposed framework is evaluated to know its effectiveness in supporting different algorithms for achieving brain tumor detection. The performance metrics used are accuracy, sensitivity and specificity. These metrics are based on the confusion matrix provided in Table 1.

Table 1: Confusion matrix

	Ground Truth (correct prediction of brain tumor)	Ground Truth (wrong prediction of brain tumor)
Result of CTANN-BTD framework (correct prediction of brain tumor)	True Positive (TP)	False Positive (FP)
Result of CTANN-BTD (wrong prediction of intrusions)	False Negative (FN)	True Negative (TN)

Table 1 shows confusion matrix that helps to understand the meaning of True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN). TP indicates correct classified positive brain tumor detection case. TN indicates correctly classified negative brain tumor detection case. FP represents incorrectly classified negative brain tumor detection case while FN indicates incorrectly classified positive brain tumor detection case. Based on TP, FP, TN and FN measures performance metrics like sensitivity, specificity and accuracy are derived. Sensitivity is nothing but true positive fraction which is computed as in Eq. 7.

$$sensitivity = \frac{TP}{TP+FN} \tag{7}$$

It indicates the probability of a person to have brain tumor disease. In the same fashion, specificity denotes true negative fraction. It means, the sensitivity value indicates the probability of a person not having brain tumor disease. It is computed as in Eq. 8.

$$specificity = \frac{TN}{TN+FP} \quad (8)$$

Accuracy is indicates whether brain tumor diagnosis is correctly performed by the framework proposed. It is computed as in Eq. 9.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

5. EXPERIMENTAL RESULTS

This section provides evaluation of results of the proposed framework. As discussed in Section 4, the metrics like accuracy, specificity and sensitivity are used for evaluation.

Table 2: Shows brain tumor detection performance of the CTANN-BTD framework

Image Size	Brain Tumor Detection Performance		
	Sensitivity %	Specificity %	Accuracy %
256x256	96.4	100	96.9
128x128	96.4	100	96.9
64x64	92.8	100	93.7

As shown in Table 2, the brain tumor detection performance for brain tumor images of different size is presented in terms of accuracy, specificity and sensitivity.

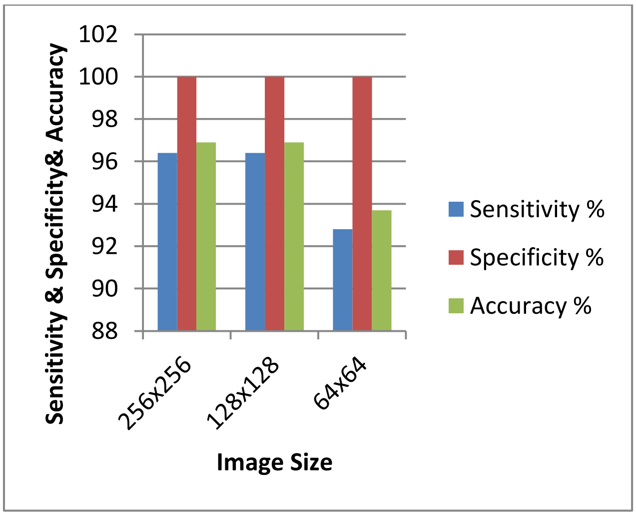

Figure 5: Performance of the framework in terms of accuracy, sensitivity and specificity

As shown in Figure 5, the sensitivity of brain tumor images of different size is evaluated. The results revealed that the proposed framework shows highest specificity.

Table 3: Shows average feature extraction time of CTANN-BTD and existing method

Image Size	Average Feature Extraction Time (sec)	
	Proposed system	Wavelet+PCA
256x256	0.47253	0.312458
128x128	0.173511	0.111235
64x64	0.069054	0.021452

As shown in Table 2, the average feature extraction timeof existing and proposed systems is presented for MRI image of different size.

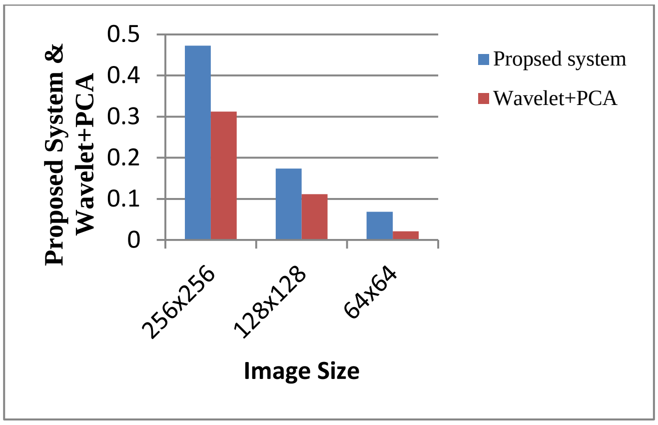

Figure 6: Performance comparison

As shown in Figure 6, the images of different size are presented in horizontal axis while vertical axis shows performance value between 0.0 and 1.0. The results revealed that the proposed system has better performance over Wavelet + PCA method.

Table 4: Shows sensitivity shown by images of different size against no. of principal components

No. of Principal Component	Sensitivity		
	64x64	128x128	256x2256
10	0.4	0.3	0.2
20	0.5	0.4	0.3
30	0.65	0.56	0.6
40	0.78	0.66	0.7
50	0.9	0.8	0.8
60	0.92	0.95	0.95
70	0.92	0.95	0.95
80	0.92	0.95	0.95
90	0.92	0.95	0.92
100	0.95	0.85	0.81

As shown in Table 4, the sensitivity of images of different size against number of principal components.

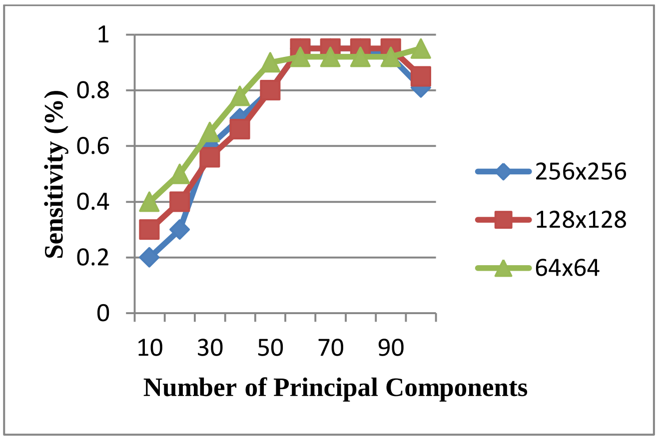

Figure 7: Performance in terms of sensitivity

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As shown in Figure 7, the number of principal components is presented in horizontal axis while vertical axis shows performance value between 0.0 and 1.0 representing sensitivity. The results revealed that the proposed system has better performance when number of principal components is increased.

Table 5: Shows specificity shown by images of different size against no. of principal components

No. of Principal Components	Specificity		
	64x64	128x128	256x2256
10	0.87	0.86	0.85
20	0.88	0.88	0.87
30	0.87	0.9	0.89
40	0.89	0.93	0.92
50	0.92	0.94	0.95
60	0.94	0.97	0.97
70	0.94	0.97	0.97
80	0.94	0.97	0.98
90	0.92	0.96	0.95
100	0.9	0.95	0.94

As shown in Table 5, the specificity of images of different size against number of principal components.

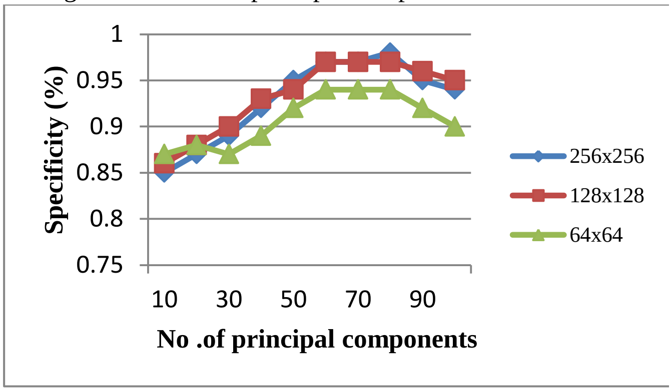

Figure 8: Performance in terms of specificity

As shown in Figure 8, the number of principal components is presented in horizontal axis while vertical axis shows performance value between 0.0 and 1.0 representing specificity. The results revealed that the proposed system has better performance when number of principal components is increased.

Table 6: Shows accuracy shown by images of different size against no. of principal components

No. of Principal Component	Accuracy (%)		
	64x64	128x128	256x2256
10	0.93	0.91	0.9
20	0.94	0.92	0.92
30	0.95	0.92	0.93
40	0.97	0.94	0.94
50	0.99	0.98	0.97
60	1	1	1
70	1	1	1
80	1	1	1
90	1	0.98	1
100	1	0.99	1

As shown in Table 5, the accuracy of images of different size against number of principal components.

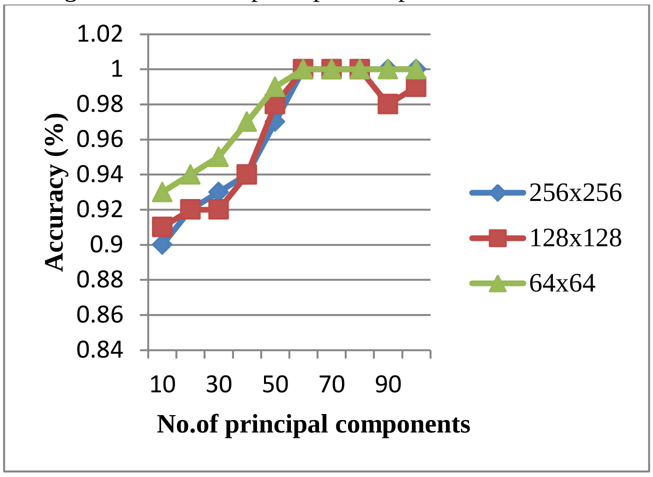

Figure 9: Performance in terms of accuracy

As shown in Figure 9, the number of principal components is presented in horizontal axis while vertical axis shows performance value between 0.0 and 1.0 representing accuracy. The results revealed that the proposed system has better performance when number of principal components is increased.

6. CONCLUSION AND FUTURE WORK

In this paper we studied the problem of brain tumor detection. From the review of literature, it is understood that Curvelet Transform based approaches are less and there is need for efficient framework that is used to diagnose brain tumor from brain MRI images. Since curvelet transform technology is able to represent directional edges and contours. Therefore, it is understood to be an ideal candidate for representing brain tumor images. Enhanced Curvelet Transform (ECT) is used for the representation of the images. A framework knownas Curvelet Transform based ANN for Brain Tumor Detection (CTANN-BTD) is proposed. The framework has functionalities like feature extraction using ECT, feature selection using PCA technique and classification using ANN. Three algorithms are defined to achieve these functionalities. They are known as ECT-FE, ECT-FS and ECT-ANN for extracting features (curvelet coefficients) from brain images, feature selection to identify most relevant features and actual classification respectively. The proposed framework is evaluated with metrics like accuracy, sensitivity and specificity. The results revealed the usefulness of the proposed framework for brain tumor diagnosis. The framework also showed better performance when compared with state of the art. In future, we intend to explore deep learning along with neural network for more efficient detection of brain tumor from MRI images.

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