AUTOMATED CLASSIFICATION OF BRAIN MRI USING COLOR-CONVERTED K-MEANS CLUSTERING SEGMENTATION AND APPLICATION OF DIFFERENT KERNEL FUNCTIONS WITH MULTI-CLASS SVM

N.Rajalakshmi
Design engineer, Sanson Engineers Ltd, Coimbatore, India
V.Lakshmi Prabha
Principal,Government College of Technology, Tamilnadu, India

Abstract:

This paper proposes a hybrid approach for classification of brain magnetic resonance images (MRI) based on color converted hybrid clustering segmentation algorithm and wrapper based feature selection with multi-class support vector machine (SVM). The texture, color and shape features have been extracted and these features are used to classify MR brain images into three categories namely normal, benign and malignant. The MR images are classified by wrapper approach with Multi class Support Vector Machine classifier (MC-SVM) using color, texture and shape features. Performance of the MC-SVM classifier is compared with different kernel functions. From the analysis and performance measures like classification accuracy, it is inferred that the brain MRI classification is best done using MC- SVM with Gaussian RBF kernel function than linear and polynomial kernel functions. The proposed system can provide best classification performance with high accuracy and low error rate.

Key Words: Magnetic resonance imaging (MRI), Color-converted segmentation algorithm, PSO+K-means clustering technique, Feature extraction, Classification accuracy, multi class Support vector machine (MC-SVM)

Introduction

This is especially true for any attempt to classify brain tissues [1]. The most important advantage of MR imaging is that it is non-invasive technique [2]. The use of computer technology in medical decision support is now widespread and pervasive across a wide range of medical area, such as cancer research, gastroenterology, brain tumors etc. [3, 4]. Fully automatic normal and diseased human brain classification from magnetic resonance images (MRI) is of great importance for research and clinical studies. In the recent past, the development of Computer Aided Diagnosis (CAD) systems for assisting the physicians for making better decisions have been the area of interest. In CAD method, computer output has been used as a second opinion for radiologist to diagnose the information with confident and quicker mechanism as compared to manual diagnosis. Pathologies are clearly identified using automated CAD system [2]. It also helps the radiologist in analyzing the digital images to bring out the possible outcomes of the disease. The developments of Computer Aided Diagnosis (CAD) systems have been focused by many researchers for providing valuable information to the radiologists. Recent work [2, 5] has shown that classification of human brain in magnetic resonance (MR) images is possible via supervised techniques such as artificial neural networks and support vector machine (SVM) [2], and unsupervised classification techniques unsupervised such as self organization map (SOM) [2] and fuzzy c-means combined with feature extraction techniques [5]. Other supervised classification techniques, such as k-nearest neighbors (k-NN) also group pixels based on their similarities in each feature image [1] can be used to classify the normal/pathological T2-wieghted MRI images. We used supervised machine learning algorithms

(ANN and MC-SVM) to obtain the classification of images under three categories, either normal or benign, malignant.

Methodolog

The proposed approach is shown in fig1. There are four major steps in the proposed approach: (1) Preprocessing (2) Color based K-means segmentation (3) Feature extraction: color, shape, texture features extracted from the segmented image (4) feature selection with classification.

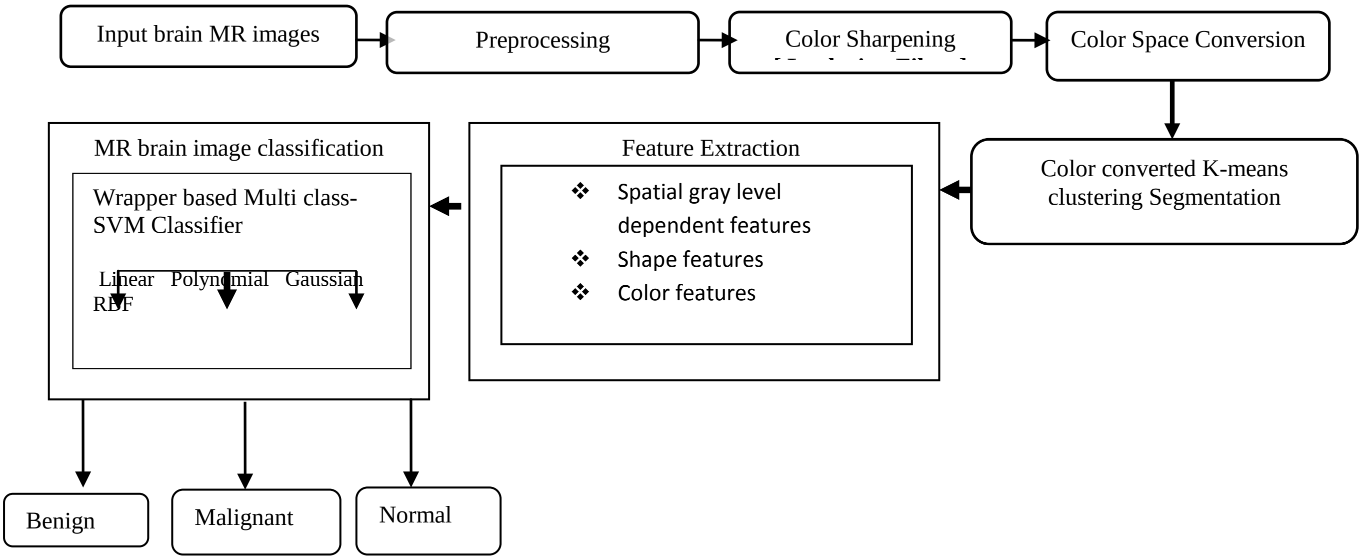

Fig1. Flowchart of proposed methodology

Preprocessing

Image denoising is a common pre-processing steps in many Magnetic Resonance (MR) image processing and analysis tasks, the goal of denoising is to remove the noise, which may corrupt an image during its acquisition or transmission, while retaining its quality. In this paper effectiveness of two denoising algorithms viz. (1) Wiener filter (2) Wavelet filter in the presence of additive white gaussian noise is compared. The Wiener filtering [6] executes an optimal tradeoff between inverse filtering and noise smoothing. It removes the additive noise and inverts the blurring simultaneously. The Wiener filtering is optimal in terms of the mean square error. In other words, it minimizes the overall mean square error in the process of inverse filtering and noise smoothing. The Wiener filtering is a linear estimation of the original image. The approach is based on a stochastic framework. Wiener method does a good job at deblurring; however, it behaves very poorly in the presence of large noise. To overcome the weakness of the Wiener filtering, Donoho and Johnstone proposed the wavelet based denoising scheme in [7].

Wavelet Thresholding approach

Steps for implementing denoising using wavelet based soft thresholding technique is as follows

- calculate two-level *haar* wavelet transform of the noisy image
- modify the noisy wavelet coefficients according to soft thresholding rule

$$w_{j,k} = \operatorname{sgn}(w_{j,k})(|w_{j,k} - t_u|) \qquad \text{if } w_{j,k} > t_u \qquad (1)$$

$$= 0 \qquad \text{if } w_{j,k} \leq t_u \qquad (2)$$

Where Donoho [12] threshold also called Universal threshold given by: $t_u = \hat{\sigma} . \sqrt{2\log(n)}$, where n is the number of wavelet coefficients, and $\hat{\sigma} = \frac{\text{MAD}}{0.6745}$ is the estimates of the noise standard deviation. MAD denotes the Median Absolute Deviation of the wavelet coefficients in the finest resolution level. The wavelet coefficients $w_{j,k}$ above the universal threshold are updated by soft thresholding: $\operatorname{sgn}(w_{j,k})(|w_{j,k} - t_u|)$. In practical applications, the variance of the noise is estimated by dividing the *MAD* by 0.6745.

- Compute the inverse *haar* wavelet transform using modified coefficients and then get denoised image.

Wavelet filter [7] removes noise pretty well in smooth regions but perform poorly along the edges. The results are compared on the basis of PSNR, SNR, and MSE. The comparisons of two denoising schemes are tabulated in Table1. It have been concluded that wavelet based techniques gives better results as compared to wiener filtering technique.

Table 1 shows comparison of two denoising schemes.Fig2 shows the output of the preprocessed image using wiener and wavelet methods. Thus the obtained results in qualitative and quantitative analysis show that this denoising algorithm based on wavelet transform outperforms the wiener method in terms of PSNR, SNR and MSE.

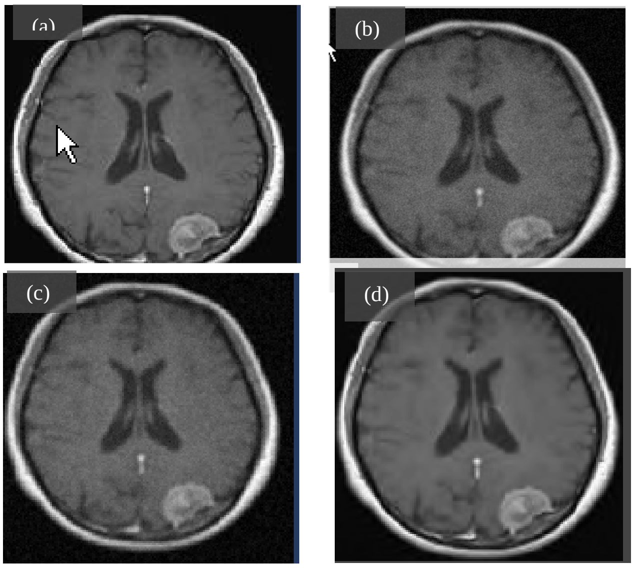

Fig2. Denoising of MR brain Image for variance=10(a)Original image(b)Noisy image(c) Denoised image with wiener filter (d) Denoised image using wavelet filter(soft threshold)

Table 1. Comparison of SNR, PSNR, MSE of denoising schemes of MR (magnetic resonance) brain image corrupted by additive white gaussian noise

Denoising schemes	Noise(σ)=10			Noise(σ)=20		
	PSNR	SNR	MSE	PSNR	SNR	MSE
Wiener Filter	20.07	10.60	639.93	19.64	10.17	706.13
Wavelet-soft thresholding	27.14	13.81	0.0034	25.16	12.61	0.0048

Color-Based Segmentation Using K-Means Clustering

Segmentation is the partition of a digital image into similar regions to simplify the image representation into something that is more meaningful and easier to analyze [8]. Pixels in the region are similar to each other with respect to some characteristic property like color, intensity or texture. In color based k-means clustering segmentation method MR gray level brain image is converted into an RGB color image by applying pseudo-color transformation a mapping function that maps a gray-level pixel to a color-level pixel by a lookup table in a predefined color map. An RGB color map contains R, G, and B values for each item. The method [9] has adopted the standard RGB color map, which gradually maps gray-level values 0 to 255 into blue-to-green-to-red color. Before transforming RGB color image into a CIE Lab color model, laplacian operator [10] has been applied to each channel in the RGB image using the equation $g(x,y)=f(x,y)+c[\nabla^2 f(x,y)]$Where $g(x,y)$ is the new sharpened image, ∇^2 is Laplacian edge detection and $c(x,y)$ in RGB color image expressed as a vector of red, green and blue image components $c(x,y) =[R(x,y),G(x,y),B(x,y)]^T$ by computing the Laplacian of individual scalar components and the output color image appears sharpened.Color based segmentation is significantly affected by the choice of color space. The general RGB color space gives high degree of detail, but it is not in tune with the normal human perception. L a'b' color space is the better representation of the color content of the image and an added advantage of L a'b' color space is that distance metric for clustering techniques continues to be Euclidean ,so we used L a'b' color space in our work. To retrieve important features to benefit the clustering process, the RGB color space is further converted to a CIELab color model. The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. This resultant features such as information in the *a***b** layers along with gabor wavelet features which is a feature vector (texture representation) created using mean and standard deviation as the feature components with scale of 6 and orientation of 4 can extract the texture frequency and orientation information effectively. So color and gabor features are feature vectors, that will be given to the clustering process as an input. Here we are using K-Means algorithm for the clustering purpose. Use K-means to cluster the objects into three clusters using the Euclidean distance metric. And then labels every pixel in the image using the results from the clustered algorithm.

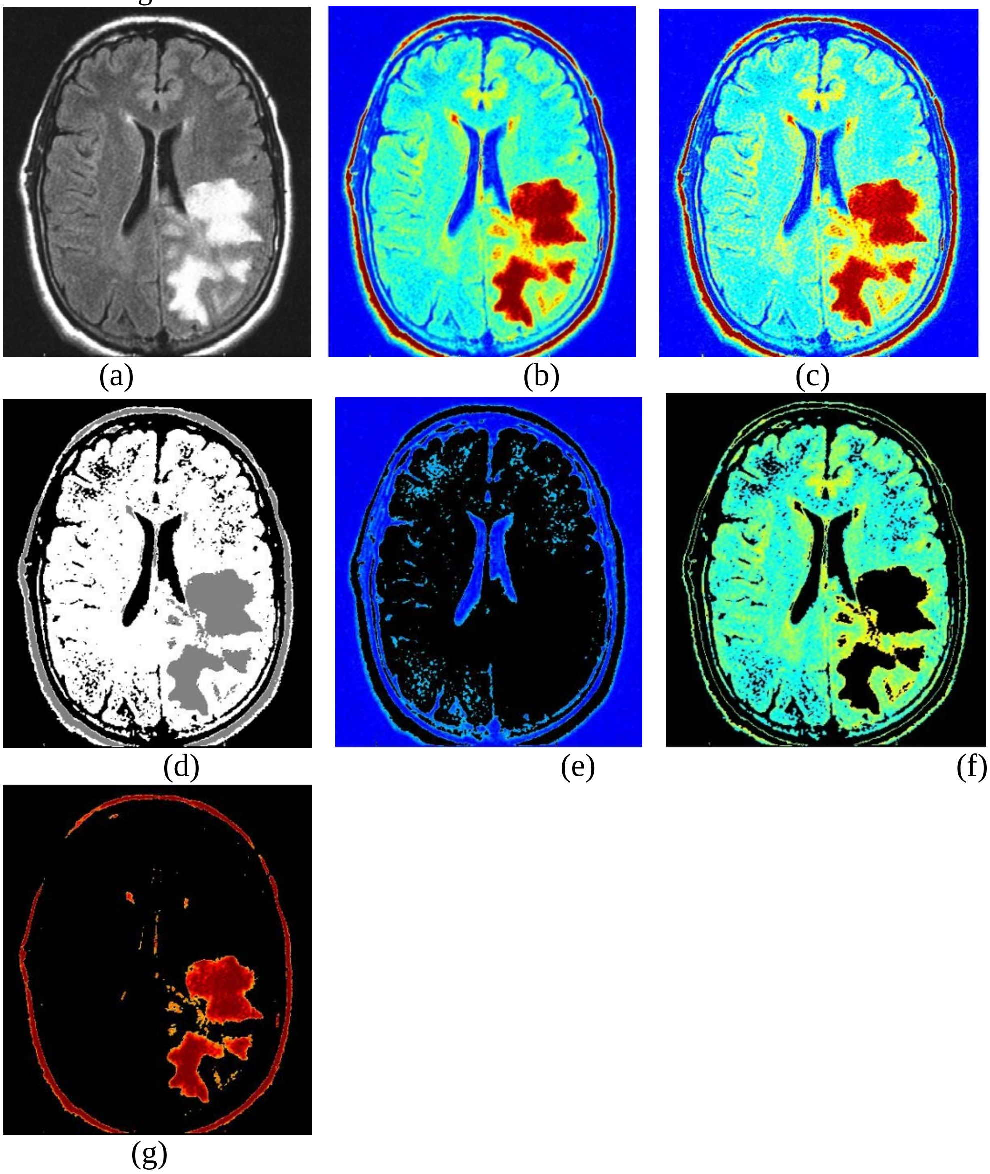

Fig 3(a) Original Gray Level Brain Image **(b)** RGB Color Space translated Image**(c)** Color sharpened image **(d)** image labeled by cluster index **(e)** objects in cluster 1**(f)** objects in cluster 2 and **(g)** final segmentation of K-means algorithm

Feature extraction

The third step of the proposed system is extracting Useful features from the image for classification purpose. It is a challenging task to extract good feature set for classification. There are many techniques for feature extraction, in this work texture, color and shape features have been considered for diagnosis.

Texture Features Extraction

A. Texture Features Extraction

Proposed system used texture feature extraction method proposed by Haralick [11], namely, the spatial gray-level dependence method (SGLDM). This well known statistical method for extracting second order texture information is based on the estimation of the second-order joint conditional probability density function[8,9] for the pixel (i, j), P(i, j | d, θ) for θ=0°, 45°, 90° and 135°. The function P(i, j | d, θ) is the probability that two pixels which are located with an inter sample distance d and a direction θ. For an offset distance *d=1*, cooccurrence matrices are calculated for offset angles of 0°, 45°, 90° and 135°. and fourteen Haralick features can be extracted.

B. Color Features

Color is one of the most widely used features. Color features can be obtained by various methods. In this work color moments [12] has been used because the Color moment method has the lowest feature vector dimension and lower computational complexity. Three Color moments features such as mean,variance and skewness are calculated for each of the Color component. Hence for each MR color space converted brain image total 9 features of Color moments are obtained

C. Shape features

Shape provides geometrical information of an object in image, it is an important visual feature and it is one of the primitive features for image content description. In this study the shape features such as Centroid, eccentricity, Euler number, solidity, convex hull, equivdiameter, orientation, extrema, and extent are considered.

Feature Selection with MC-SVM

The numbers of texture, color and shape features extracted from the MR brain image can be irrelevant or redundant. Feature reduction improves classification by searching for the best features subset, from the fixed set of the original features, according to a given processing goal and a feature evaluation criterion: classification accuracy. Hence to reduce the large numbers of features to a smaller set of features in this work we used wrapper algorithm with multi-class SVM.

Multi-class support vector machine (MCSVM) classifier

Model Selection for Support Vector Machines

Model selection is a crucial part for SVMs classifier design and still an ongoing research issue. This usually involves the kernel and the corresponding parameters selection. In our proposed methodology, we have used one-against-all multi-class SVM [13, 14] (MC-SVM) with following kernel functions such as

- $Linear\ kernel: K(x_{i,}x_j) = 1 + x_i{}^T\, x_j$
- $Polynomial\ kerenel: K(x_{i,}x_j) = (1 + x_i{}^T\, x_j)^p$
- $Gaussian\ Radial\ basis\ Function(\ RBF)$:$\exp\left[\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right]$

In this article, we propose a feature ranking based wrapper algorithm [15] for multi-class SVM classification. Feature ranking is achieved by Information theoretic ranking criterion. In our proposed methodology, we have used one-against-all multi-class SVM (MC-SVM) with gaussian RBF kernel function which is as follows;$Gaussian\ Radial\ basis\ Function(\ RBF)$:$\exp\left[\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right]$, and we applied a grid search with 10-fold cross validation process to select the optimal parameters in this paper. Range values for C and sigma tested were 1 ≤C ≤100 and 0.05 ≤ σ (sigma) ≤2. Optimal values were experimentally determined equal to C= 10 and sigma = 0.5. The procedure is summarized below

- Apply feature ranking technique on dataset using mutual information. Feature ranking is provided by Information theoretic ranking criterion. To measure the non linear dependencies between a feature and the target, mutual information between each feature and the target is investigated in information theoretic approach.

The mutual information is defined by entropy I as:

- $I(i) = \int_{x_i} \int_{y} p(x_i, y) \log \frac{p(x_i, y)}{p(x_i) p(y)} dx dy$

  (33)

  Where $p(xi)$ and $p(y)$ are the probability densities of xi and y, and $p(xi, y)$ is the joint density. The criterion $I(i)$ is a measure of dependency between the density of variable xi and the density of the target y.
- Select top k features and train MC-SVM with top k features then evaluate 10 fold cross validation accuracy.
- Select k+i features and evaluate MC-SVM
- Repeat step 3 until the accuracy of k+i≥k
- Set maximum classification accuracy from the wrapper approach classification.

Results and Discussion

Twenty three Scans containing normal brain, twenty five scans containing benign tumor and hundred and two scan containing malignant T1-weighted brain tumor images were obtained from hospitals in Coimbatore and have been considered for this work. The images under study were acquired using the Siemens 1.5-Tesla MR Systems. Initially MR images are subjected to preprocessing using wiener filter. The performance of this filter is compared with wavelet filter method and shown in table 1. Fig2 shows the output of the preprocessed image using wiener and wavelet transform. It is seen that the wavelet performs well. Once the preprocessing is done convert all the MRI images into a RGB color space images then laplacian sharpening operator is applied to RGB color images in order to enhance both the intensity and the edge of the images. To retrieve important features to benefit the clustering process, the RGB color space is further converted to a CIE Lab color model. Segmentation was done by color based K-means approach .The sample image considered in this work and their respective outputs after RGB color space conversion,color sharpening and K-means Clustering Segmentation are shown in fig 3,4 .For the feature extraction step texture, color and shape features were estimated . In the proposed system 12 SGLDM measures with offset distance of 1 and offset angles of 0°, 45°, 90° and 135°are derived and nine color, nine shape features were extracted and used for obtaining optimized feature set. The wrapper algorithm with MC-SVM classification used to classify the input features into normal, benign or malignant. In the classification step MC-SVM with Gaussian RBF kernel is compared with linear and polynomial kernel functions. It can be concluded from the experimental results that Gaussian RBF kernel based MC-SVM is a promising technique for MRI brain image classification and give high classification accuracy with low error rate.

The performance of the proposed method has been evaluated in terms of sensitivity, specificity and accuracy. Table 2 represents the performance comparison for classifier with different kernel functions. Here total 150 images are taken for training and testing. Among 150 images the Normal category is 23 images, benign 25 images, malignant 102 images are taken for training and testing which is classified using color based K-means and MC-SVM with different kernel functions. The results show that the proposed system with Gaussian RBF give better percentage of classification while compared to MC-SVM classifier with linear and polynomial kernel functions. Table 3 illustrates the classification accuracy, sensitivity, specificity, area under curve and standard error for performing the proposed approach by using the common kernel functions including linear, polynomial and gaussian RBF. The experimental results have shown that the proposed method with gaussian RBF achieves good classification accuracy and less standard error while compared to MC-SVM classifier with linear and polynomial kernel functions. Therefore, it can be concluded that Gaussian RBF kernel based MC-SVM is a promising technique for MRI brain image classification

The Receiver Operating Characteristic (ROC) curves are plotted with respect to sensitivity and specificity. The area under the ROC (AUC) curve is an important parameter to determine the overall classification accuracy of the proposed system. Fig 4 shows the comparison of ROC plot for MC-SVM classifier with linear, polynomial, Gaussian RBF kernel functions. It has been seen that, proposed method with Gaussian RBF has the highest (0.91) AUC whereas the other method give lesser (0.89, 0.86) value. Hence, proposed method provides a higher accuracy than other method.

lasses	No. of data for training/testing	Number of correctly classified data			Percentage of correct classification		
		Color based K-means with MC-SVM(Gaussian RBF)	Color based K-means with MC-SVM(Poly)	Color based K-means with MC-SVM(Lin)	Color based K-means with MC-SVM(Gaussian RBF)	Color based K-means with MC-SVM(Poly)	Color based K-means with MC-SVM(Lin)
Normal	23/23	19	18	16	82.6	81.7	79.9
Benign	25/25	23	23	21	92.4	92.4	89.3
Malignant	102/102	99	98	96	98.7	97.1	95.1
Average					91.6	90.5	88.5

Legend: Lin - Linear; Poly - Polynomial; RBF - Radial basis function

Table 2. Performance of the classifier

Classification Technique	Kernel used	Sensitivity %	Specificity %	Accuracy%	AUC	Standard error
Color based K-means with MC-SVM(color+texture+shape features)	Linear	90.12	80.54	89.17	0.86	0.04046
Color based K-means with MC-SVM(color+texture+shape features)	Polynomial	91.87	83.92	91.7	0.89	0.03924
Color based K-means with MC-SVM(color+texture+shape features)	Gaussian RBF	92.13	84.12	92.6	0.91	0.03340

Table 3. Results of the classifier

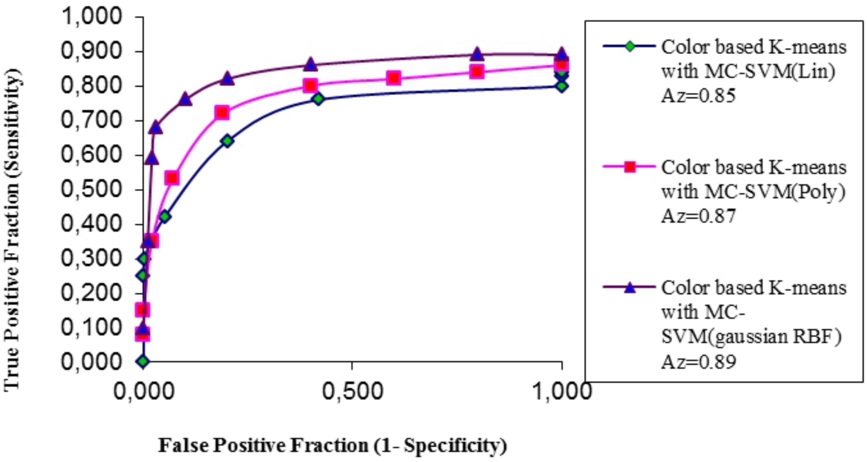

Fig 4.ROC analysis for tumor classification system

Conclusion

An improved automated classification technique using color-converted K-means clustering segmentation algorithm and wrapper algorithm with Multi-class SVM classifier with linear, polynomial, Gaussian RBF kernel functions for classifying Brain MRI as normal or abnormal (benign or malignant tumor) has been proposed and the performance is evaluated. It is concluded from the analysis that the multiple features, color converted K-means segmentation approach, the wrapper approach MC-SVM with Gaussian RBF kernel function enhance the classification of MR brain image with normal and benign or malignant classes The proposed approach is efficient for classification of the human brain normal or abnormal (benign or malignant tumor) with high sensitivity, specificity and accuracy rates.

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