corpus callosum have been the focus of investigation for many DTI studies examining white matter integrity in schizophrenia given its importance to neurobiological models of the disorder and ease of identification. Across voxelwise, region-of-interest, and tractography based analyses of DTI data, evidence has accumulated indicating that this region is abnormal in schizophrenia.

The splenium, in particular, has been identified as an area of abnormally low FA in patients with schizophrenia relative to controls studied by Agartz and et al., in 2001. Grabczewski. K and et al., (2005) [8] discussed two feature selection algorithms, which take advantage of a decision tree criterion. Effective and versatile classification cannot be achieved by single classification algorithms. They must be hybrid complex models comprising a feature selection stage. Similarly to other data analysis tasks, also in feature selection it is very beneficial to take advantage of different kinds of algorithms. One of the great features of decision tree algorithms is that they inherently estimate a suitability of features for separation of objects representing different classes. This facility can be directly exploited for the purpose of feature selection. Based on the Separability of Split Value criterion, two algorithms of ranking features are reviewed. The methods are applied to a number of publicly available datasets and the results are compared to those obtained with some most commonly used feature selection techniques.

3 Proposed Scheme

The overall process of the proposed system is depicted in Figure 5 which contains MRI image pre-processing, image segmentation, feature extraction and classification. The sagittal view of the 158 MR brain images is obtained from the oasis dataset.

3.1 Image Enhancement (Pre-processing)

In our proposed system, the corpus Callosum which is located at the centre of the brain comprises white matter tissue (i.e. the pixel represented corpus Callosum has high intensity values). Portions of the corpus callosum boundary are indistinct, which make it difficult to apply segmentation algorithm based on edge information alone. Thus, a pixel intensity value histogram of the corpus callosum derived from MR brain images where the corpus callosum is very well defined and easy to segement. A variation of Cour and shi's algorithm is therefore developed that applied a threshold interval to extract objects with the same intensity values (such as corpus callosum) during the application of segmentation [6]. The corpus callosum have high pixel intensity value. Later, the result of the threshold interval is applied with pixel normalization. This method is applied to images with poor contrast due to glare. The image is normalized before applying segmentation algorithm. The method improves the brightness of the image. The pixel normalization performs two steps:

1: The minimum and maximum brightness of the image is computed

2: The normalization is applied to every pixel

The output image is stored in the database for the segmentation process.

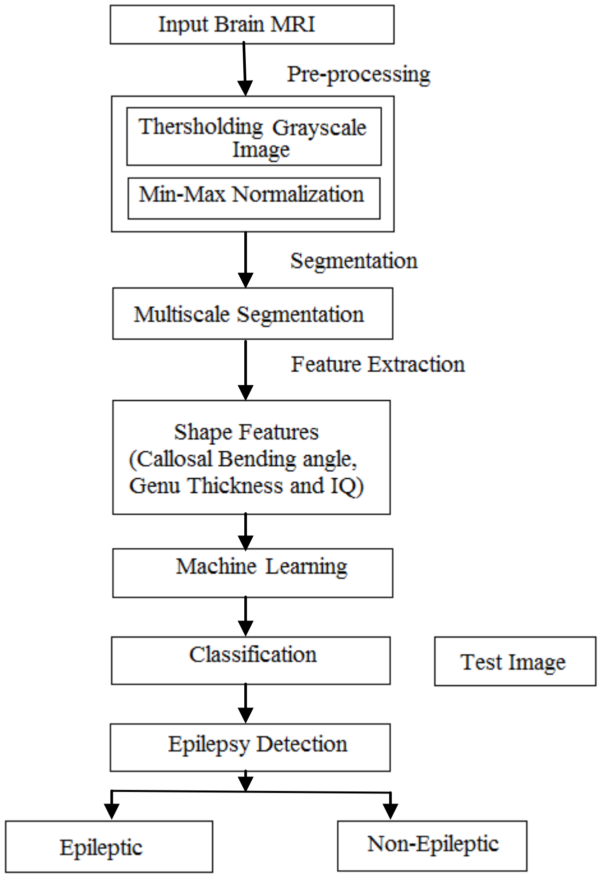

Figure 5. Overall Process of the System

3.2 Image Segmentation

Corpus callosum is a commissural fiber bundle with a specific diffusion pattern which can be coded as prior knowledge in the segmentation framework. Using this information, we prevent the hyper-surface from propagating into adjacent white matter structures such as cingulum, tapetum, minor and major forceps, and tracts of the corona radiata. Using the fact that the diffusivity in corpus callosum is perpendicular to the mid-sagittal plane of the brain, we consider a threshold (PDDx Threshold) for the x-component (left-right component) of the PDD (PDDx(r)) for propagating the front only inside the corpus callosum. The x-component of the PDD is large throughout the structure body [6]. However, corpus callosum fibers project to the cortical area at its genu and splenium, where the x-component of PDD is not large anymore [12]. Fortunately, these fibers are considered as different fiber tracts of minor and major forceps, and most of the studies investigating the different diffusion indices within the corpus callosum, exclude the minor and major forceps from that.

The proposed segmentation steps are as follows:

S1: The initial seeds in corpus callosum of midsagittal plane have been selected

S2: The hyper-surface as the congregation of small spheres around the seed points is intiated.

S3: Signed distance map from mask was created

S4: The interior and exterior mean was found using equation (1)

$$F= (I(id_x)-u)^2-((I(id_x)-v) \qquad (1)$$

S5: Until convergence the following is continued, For each point r on the hyper-surface at step t:

a) The normal direction to the surface have been calculated

b) The 26-neighborhood points are calculated and the neighbors n_r for r, which are collinear with the normal, with respect to the r.

S6: Curve is evolved and the corpus Callosum is segmented.

3.3 Feature Extraction

The shape features are used to detect masses. The shape features are also called geometric features or morphological features. These types of features are based on the shape of ROI. The feature does not consider the intensity of the pixels in the region. It will take the shape of segmented region. The Corpus Callosum is automatically segmented from the Brain MRI. The line segment was defined by dividing the upper and lower surfaces of the callosum into 40 equidistant portions by 39 nodes.

The midpoints between corresponding nodes on the upper and lower surfaces were identified. The line segment was created by joining endpoints and successive midpoints. Once the optimum endpoints and corresponding midpoints are identified, a smooth curve joining them was obtained with cubic spline interpolation, and the anteroposterior length of this curve was measured (callosal length). This curve is divided into 40 segments of equal lengths by 39 nodes. At each node, the line orthogonal to the curve is calculated. The distance between its intersection with the dorsal and ventral surfaces of the Callosum represented regional callosal thickness at these 39 points, and the mean of these 39 regional thicknesses represented mean callosal thickness. Finally, a simple measure of curvature, the callosal bending angle, is obtained by measuring the angle between two vectors, each joining the midpoint, along the mid-spline of the callosum. Mean thickness in the anterior genu is significant predicator of transition to epilepsy. The variation in the thickness of the genu of corpus callosum in the selected subjects having epilepsy was compared to normal subjects. The chief measure types are visually illustrated in Figure 6. Parcellation of the corpus callosum (CC) in the midsagittal cross-section of the brain is of upmost importance for diffusion properties. The method uses the watershed transform from markers, and the choice of markers is based only on the diffusion properties inside the corpus callosum of each subject.

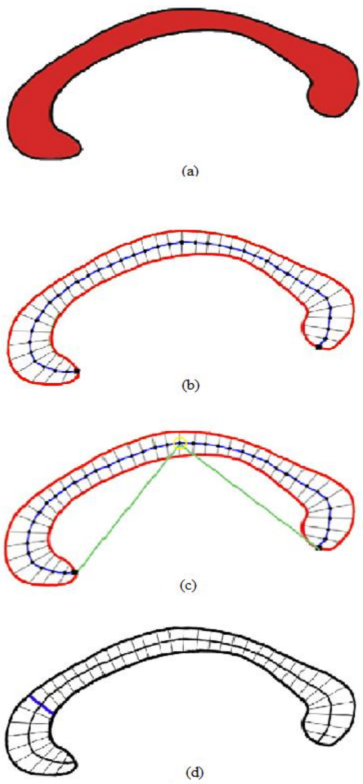

Figure 6. (a) Segmenting corpus callousm from mid-sagittal view (b) obtaing mid points and end points by traversing mid-spline in corpus callosum (c) Bending angle of corpus callosum (d) Measuring thickness of genu.

3.4 Classification

Classification is one of the most frequently encountered decision making tasks of human activity. A classification problem occurs when an object needs to be assigned into a predefined group or class based on a number of observed attributes related to that object. The individual observations are analyzed into a set of quantifiable properties, known as various explanatory variables, features, etc. Classification can be thought of as two separate problems - binary classification and multiclass classification. In binary classification, a better understood task, only two classes are involved, whereas in multiclass classification involves several classes. Since many classification methods have been developed specifically for binary classification, multiclass classification often requires the combined use of multiple binary classifiers. Implemented classification models include CBR, Support Vector Machine (SVM), Decision Tree, Bayes and Neural Network.

Case-based reasoning is used for classification. Case Based Reasoning can be defined as the methodology for solving problems by utilizing previous experiences CBR uses a similar philosophy to that which humans sometimes use. It tries to solve new cases of a problem by using old previously solved cases. In case-based reasoning, the training cases are stored and accessed to solve a new problem. Key concept in the whole system is to retrieve the similar cases. Similarity between two cases is computed using k-Nearest Neighbour (NN) algorithm. The main components of CBR are database of previous cases, solution retrieval of previous cases and obtaining the solution.

This model is called as R^4 model of CBR. Because this model can be represented by schematic cycle which contains four Rs.

1 *Retrieve* the most similar cases
2 *Reuse* the cases to attempt to solve the problem
3 *Revise* the proposed solution
4 *Retain* the new solution as a part of a new case

A new problem is solved by retrieving one or more previously experienced cases in the case base, reusing the case in one way or another, revising the solution based in reusing a pervious case, and retaining the new experience by incorporating it into the existing case base. Each process involves a number of more specific steps, for example, retrieve involves, identify, search, match and select.

Other classification algorithms includes support vector machine (SVM) which is related to supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. Given a set of training images, each image marked as belonging to one of two categories, SVM training algorithm builds a model that assigns new images into one category or the other.

A decision tree is a decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. Decision trees are commonly used in operations research, specifically in decision analysis, to help identify a strategy most likely to reach a goal.Neural networks have emerged as an important tool for classification. The recent vast research activities in neural classification have established that neural networks are a promising alternative to various conventional classification methods.A naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions. A more descriptive term for the underlying probability model would be "independent feature model".

4 Experimental Results

The performance of the proposed system is demonstrated using a MATLAB 2010b platform. A dataset of 250 images are taken from the oasis dataset [3]. Figure 7. shows the medial view of the brain MRI scan of size 256*256 which is the input. The cerebrum is divided into the left and right hemispheres, each consists of four lobes: frontal, parietal, occipital, and temporal. The corpus callosum is the one that connects the left and right hemisphere. The pre-processing of the MRI brain image is performed by using threshold grayscale interval method. Figure 8. depicts the histogram of the pixel greyscale values of the input image. Figure 9. shows that the corpus callosum can barely be recognized with a threshold interval of [0-80].

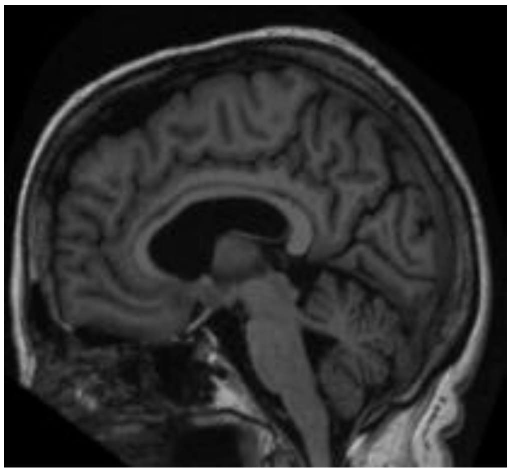

Figure 7. Medial view of MRI Brain

With a threshold interval of [0-91], the corpus Callosum is clearly defined. The corpus Callosum starts to "blur" into the surrounding tissues using a threshold interval more than 91. The significance here is that the high intensity of the corpus callosum can be exploited to yield a segmentation algorithm that is both effective and efficient across the input image set.

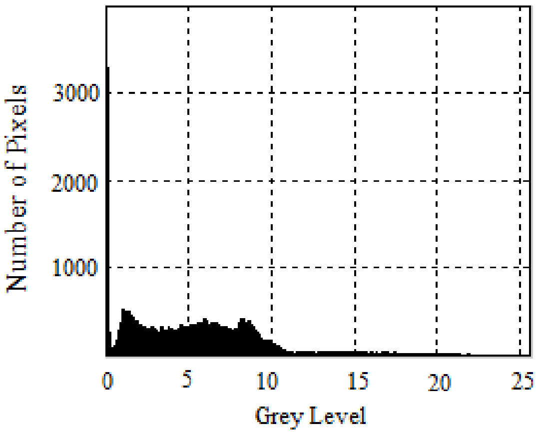

Figure 8. Histogram of the pixel greyscale values

Multiscale segmentation is applied on the pre-processed image. Figure 10 describs the segmenting process of the corpus callosum. Then at next stage the extracted corpus callosum is obtained which is depicted in the figure 11. Figure 12. shows the midpoint extraction and the angle extraction from the segmented corpus callosum. The shape features are extracted. The shape features obtained in the corpus callosum are genu thickeness, the mid-sagittal angle and the Intelligent Quotient (IQ). Unitary callosal measures such as callosal length and callosal bending angle were compared between groups.

(a) Thershold Interval between [0-80]

(b) Thershold Interval between [0-91]

(c) Thershold Interval between [92-110]

Figure 9. Thresholding with various threshold intervals

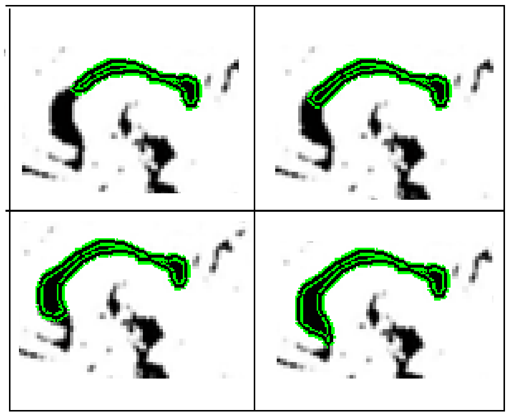

Figure 10. The Segmenting process of corpus Callosum

Figure 11. Segmented corpus Callosum

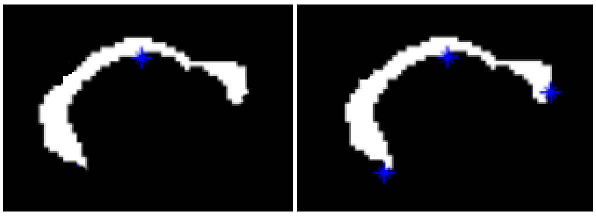

Figure 12. (a) Midpoint extraction (b) Angle extraction from segmented corpus Callosum

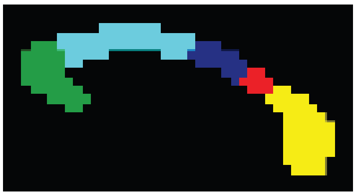

Figure 13. Parcellation of corpus Callosum

The statistical measure of the corpus callosal bending angle is within the angle 91.34 – 109. The Genu overall thickness is 1.0 mm – 3.5 mm. Mean thickness in the anterior genu is a significant predictor of transition to epilepsy. The genu thickness is calculated with the help of parcellation. Once the segmentation of the corpus callosum is performed in the midsagittal slice of the brain, the parcellation can be done. Parcellation is carried out by watershed transform which is depicted in Figure 13.

The accuracy of segmentation methods are compared based on entropy [13]. The entropy of an image can be defined as a measure of the uncertainty associated with a random variable and it quantifies in the sense of an expected value, the information contained in a message. Entropy of an image E returns a scalar value representing the entropy of grayscale image I. The Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined using equation (2)

$$\text{Entropy} = \sum_i -p_i \log_2 p_i \qquad (2)$$

where p_i is the probability of event i. The accuracy comparison based on entropy of various segmentation algorithms are depicted in the table 1. and figure 14. The comparison of segmentation methods based on execution time is tabulated in table 2 which shows Multiscale segmentation has less execution time compared to other traditional methods. Figure 15. depicts the corresponding graphical representation.

Table 1. Accuracy of Segmentation algorithms

Segmentation methods	**Accuracy Based on Entropy**
Edge based technique	0.7923
k-means clustering	0.7768
Region grow method	0.33251
Marker controlled watershed	0.8176
Wavelet Db16	0.55467
Multiscale segmentation	0.9151

In the next stage of the comparison, MR images were segmented and the correct boundary of the corpus callosum was identified. Then, for detailed analysis the amount of false negatives and the amount of false positives of all resultant images were calculated [7]. Completeness can be defined as the percentage of the complete region extracted by the segmentation algorithm and can be calculated using the equation 3.

$$\text{Completeness (\%)} = TP/(TP+FN)*100 \qquad (3)$$

where, TP-True Positive, FN-False Negative, TN-True Negative, FP-False Positive.

Correctness can be defined as the percentage of correctly extracted region by the segmentation algorithm and can be calculated using,

$$\text{Correctness (\%)} = TP/(TP+FP)*100 \qquad (4)$$

Table 2. Execution time Comparison

Segmentation Method	**Execution time (in sec)**
Edge based technique	1.32
k-means clustering	1.02
Region grow method	1.67
Marker controlled watershed	1.56
Wavelet Db16	1.05
Multiscale Segmentation	0.86

Table 3 depicts the calculated values of correctness and completeness of the segmentation methods. From the result, the correctness and the completeness measure of the Multiscale segmentation greater than 95%. So this can be considered as the suitable method for the segmentation of 2D magnetic resonance images. Figure 15. shows the comparison of the Correctness in segmentation methods. Figure 16. shows the comparison of the Completness in segmentation methods.

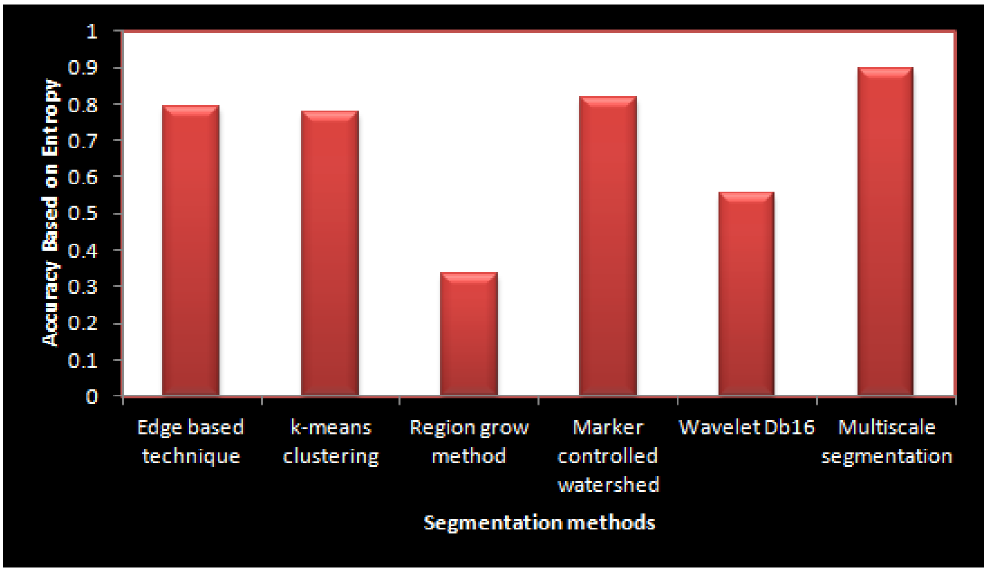

Figure 15. Comparison of Segmenation Accuracy

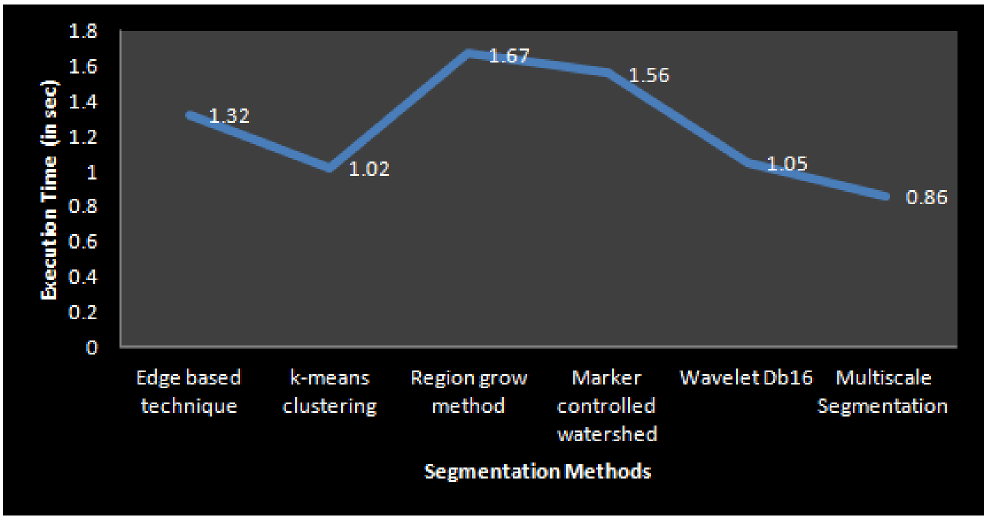

Figure 15. Execution time comparison of Segmentation methods

Table 3. Completeness and Correctness of Segmentation methods

Segmentation methods	**Completeness (%)**	**Correctness (%)**
Edge based technique	84	71
k-means clustering	98	83
Region grow method	96	90
Marker controlled watershed	83	81
Wavelet Db16	91	92
Multiscale segmentation	99.2	96.5

In this paper, classification algorithms are evaluated in terms of sensitivity (*Se*), specificity (*Sp*) and accuracy (*Acc*). The values are tabulated in table 4. The metrics are defined as,

$$Se = TP/ (TP+FN) \quad (4)$$

$$Sp = TP/ (TN+FP) \quad (5)$$

$$Acc= TP+TN/ (TP+FN+TN+FP) \quad (6)$$

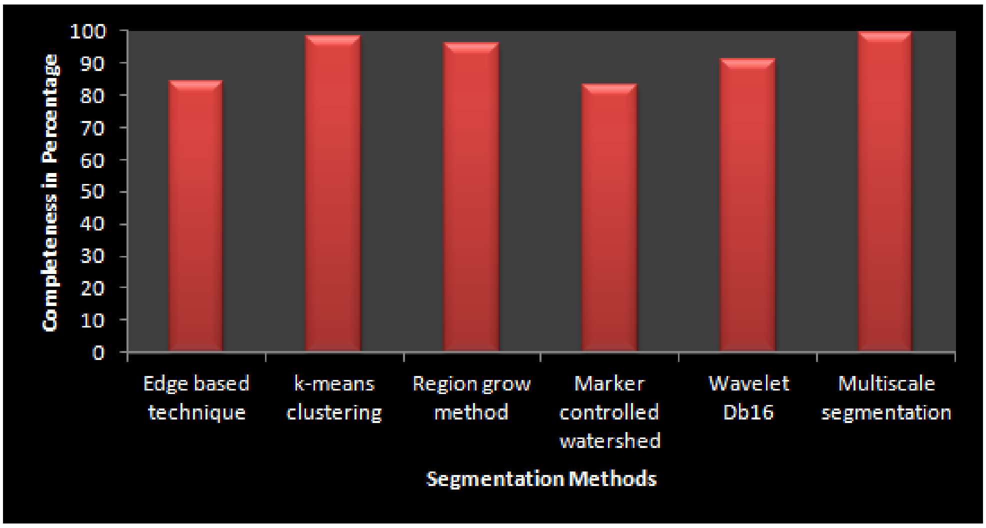

Figure 15. Comparison of segmentation methods based on completeness

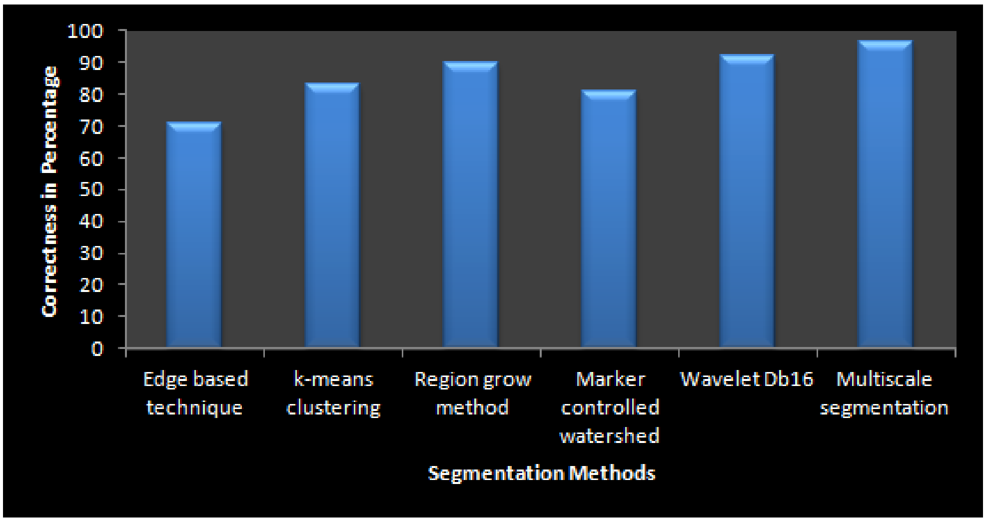

Figure 15. Comparison of segmentation methods based on correctness

where, TP-True Positive, FN-False Negative, TN-True Negative, FP-False Positive. The performance results shows that CBR provides sensitivity *(Se)* of 97%, specificity *(Sp)* of 89% and overall accuracy *(Acc)* of 96.7% when compared to SVM, Decision Tree, Bayes and Neural Network. Figures 16 shows the comparison results of classification models in terms of *Se*, *Sp* and *Acc*.

Table 4. Performance results of Classification model

S.No	Classification Model	Sensitivity (%)	Specificity (%)	Accuracy (%)
1	Case Based Resoning	97	89	96.7
2	Decision Tree	87	73	81
3	SVM	93	89	95.6
4	Neural Networks	86	70	78
5	Bayes	90	69	82

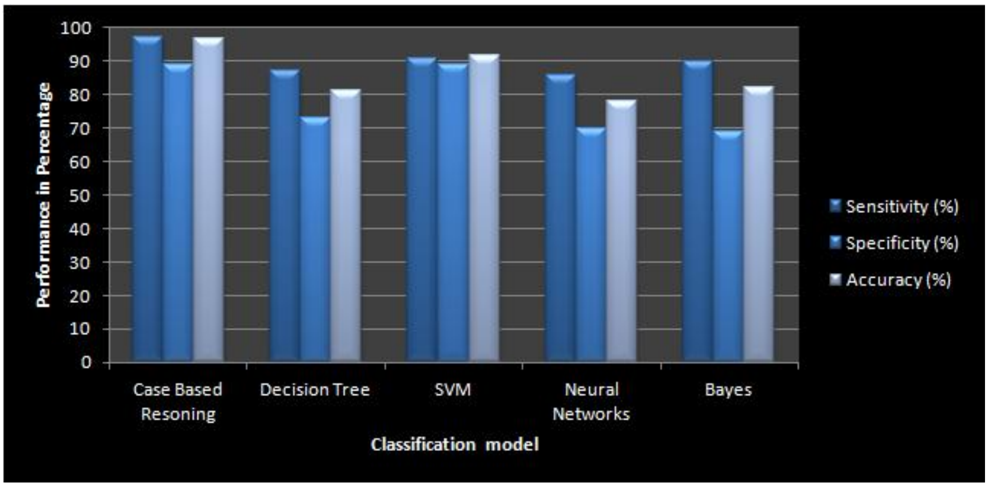

Figure 16. Comparing Se, Sp and Acc of Classification Models

5 Conclusion

The proposed system is used to segment the corpus Callosum and to extract shape features from the corpus callosum. The classification of epileptic and non-epileptic patients using Case Based Reasoning classification model has been proposed. This paper compares well-known classification models with CBR. Also, it compares six gray-level image segmentation methods to identify the most suitable method for the segmentation of corpus callosum. Multiscale segmentation has less execution time compared to other methods for segmentation. From the experimental results obtained it is concluded that the threshold interval method is best for the pre-processing, the Multiscale segmentation is suitable for segmentation and Case Based Resoning is suitable for the classification of the epileptic images from normal images. Thus, through these methods less false positive rate and improved prediction accuracy in diagnosing epilepsy has been achieved.

References:

[1] Ayelet Akselrod-Ballin, Meirav Galun, John Moshe Gomori, Massimo Filippi, Paola Valsasina, Ronen Basri and Achi Brandt ‘Automatic segmentation and classification of multiple sclerosis in multichannel MRI’, IEEE Transactions On Biomedical Engineering, Vol. 56, No. 10, October 2009.

[2] Anitha. M, Tamije Selvy. P and Palanisamy. V, ‘WML Detection of Brain Images Using Fuzzy and Possibilistic Approach in Feature Space’, WSEAS Transactions On Computers, Issue 6, Volume 11, June 2012

[3] Brain data set ‘ http:// www. oasis.com’

[4] Da la court, A., Breteler,M.M., and Meinardi,H et al,‘ Prevalence of Epilepsy in The Elderly: The Rotterdam Study’, Epilepsia , Vol. 37, No.2, pp.141-147,1996

[5] Debashis Ganguly, Srabonti Chakraborty and Tai-hoon Kim, ‘A Cognitive Study on Medical Imaging’, International Journal of Bio-Science and Bio-Technology, Vol. 2, No. 3, September, 2010

[6] Elsayed .A , F. Coenen, C. Jiang, M. García-Fiñana and V. Sluming , ‘Corpus callosum MR image classification’, Knowledge-Based Systems, Vol. 23, pp. 330–336, 2010.

[7] Gajanayake, Randike, Yapa, Roshan Dharshana, and Hewavithana, Badra , ‘Comparison of standard image segmentation methods for segmentation of brain tumors from 2D MR images’, In Proceedings of the 4th International Conference on Industrial and Information Systems, ICIIS 2009,IEEE, University of Peradeniya, Sri Lanka, pp. 301-305, 2009

[8] Grabczewski. K and et al., ‘Feature selection with decision tree criterion’, Fifth International Conference on Hybrid Intelligent Systems, HIS '05, 2005.

[9] Juliana S. Bloom and George W. Hynd ‘The role of corpus callosum in interhemisphere Transfer of Information: Excitation or Inhibition?’, Neuropsychology Review, Vol. 15, No. 2, June 2005

[10] Leon Kier .E and Charles L. Truwit , 'the normal and abnormal genu of the corpus callosum: An evolutionary , Embryologic, anatomic, and MR analysis' , American Society of Neuroradiology, Vol.17, pp.1631–1641, Oct 1996

[11] Michael D HILLS, 'The psychological and social impact of epilepsy',Neurology Asia 2007; Vol. 12: pp. 10 – 12

[12] Nazem-Zadeh et al. 'Segmentation of corpus callosum using diffusin tensor imaging: validation in patients with glioblastoma', BMC Medical Imaging 2012, Vol 12 No.10, 2012.

[13] Prasantha H.S et. al. ' Medical Image Segmentation', International Journal on Computer Science and Engineering Vol. 02, No. 04, 2010, 1209-1218

[14] Ruben I. Kuzniecky and Graeme D. Jackson, ' Magnetic resonance in epilepsy', Neuro Imaging Techniques 2nd Edition, 2011

[15] Woodruff PW, McManus IC and David A.S, 'Meta-analysis of corpus callosum size in schizophrenia', Journal of Neurol Neurosurg Psychiatry, Vol .58, No. 4, pp.457–461, 1995