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GRAY LEVEL CO- OCCURRENCE MATRIX FEATURES BASED CLASSIFICATION OF TUMOR IN MEDICAL IMAGES

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ABSTRACT

In this paper, the classification of Brain Magnetic Resonance Images (MRI) and Liver Computed Tomography (CT) images has been analysed using supervised technique. The proposed method includes four stages - pre-processing, fuzzy clustering, feature extraction and classification. For extracting the features Gray Level Co-occurrence Matrix (GLCM) method has been used. The main features regarding shape, texture and feature statistics have been considered. Then the classifier has been used to classify the brain MRI and the CT liver images into normal and abnormal. The classifier used was Radial Basis Function - Support Vector Machine (RBF-SVM). Finally, the performance of the classifier was evaluated in terms of True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) and the accuracy was found to be good.

Keywords: fuzzy clustering, GLCM features, features extraction, classification, MRI brain images, CT Liver images, Segmentation.

1. INTRODUCTION

The magnetic resonance imaging (MRI) is an important medical imaging technique, used by the radiologists to visualize the internal structure of the body. MRI provides much contrast between different soft tissues of body. Due to these characteristics, MRI plays a vital role in neurological studies. Brain tissue classification technique is used for the detection of pathological conditions affecting the brain structure. The interesting tissues in brain are White matter, Gray matter, and Cerebro spinal fluid the classification of human brain images can be done either by using supervised techniques or un-supervised techniques. Heydy Castillejos *et al.* [1] explained about the concept of segmentation using fuzzy clustering. D. Selvaraj *et al.* [2] reviewed various current technologies of brain image segmentation by using automated algorithms along with their advantages and disadvantages. This helps in combining two or more methods together to produce accurate results.

S.N. Deepa *et a*l. [3] surveyed the applications of intelligent computing techniques for bio-medical image classification and discussed on how Artificial Neural Network is utilized for image classification over generations. Chun *et al.* [4] used Discrete Wavelet Transform to extract features, PCA to reduce the number of features and adaptive back propogation neural network as a classifier to classify the brain magnetic resonance images as normal or abnormal J.Jiang et al. [5] discussed how a neural network with fixed structure and training procedure could be applied and expanded further to resolve problems relevant to medical imaging. Dipali M.Joshi *et al.* [6] designed a neuro- fuzzy classifier using artificial neural network to recognize different types of brain cancers. In that, texture features are extracted from tumor region and compared with the stored features in the knowledge base. Dayong *et al.* [7] employed wavelet transform to extract features from images, principal component analysis to reduce the dimensions of features and back propogation neural network to recognize the brain state. Mohd Fauzi *et al.* [8] used probabilistic neural network for brain tumor classification and principal component analysis to extract features from images. It has been concluded that probabilistic neural network gave fast and accurate classification of the tumors. D. Jude Hemanth *et al.* [9] performed modifications in the training methodology of conventional Counter Propogation Neural Network (CPNN) and kohonen networks, in order to make ANN iteration free with improved convergence rate besides yielding accurate results.

M. Saritha *et al.* [10] integrated wavelet entropy based spider web plots and probabilistic neural network for the classification of Magnetic Resonance (MR) brain images, the spider web plot is a geometric construction drawn using the entropy of the wavelet approximation components, and the area calculated are used as feature set for classification. Tong et al. [11] followed a multiple instance learning method to detect Alzheimer's disease. In this work the local intensity patches are extracted as features and a graph was built for each image. Yudong zhang *et al* [12]. Employed wavelet transform to extract features from the images and principle component analysis to reduce the dimensions of features, the reduced features are applied to back propogation neural network with scaled conjugate gradient to find the optimal weights of neural network. Lynn M. Fletcher-Heath et al. [13] presented an automatic segmentation of non-enhancing brain tumors from healthy tissues in magnetic resonance images. An initial segmentation was computed by using an unsupervised fuzzy clustering algorithm. Then, the integrated domain knowledge and image processing techniques were applied under the control of a knowledge-based system. Nan Zhang et al. [14] presented a framework by fusing multi-spectral brain MR images, to extract the most useful features to obtain the best segmentation with the least cost in time. The Support Vector Machine (SVM) classification was proposed.

B. Sowmya *et al.* [15] explained the process of segmenting any given colour image using fuzzy clustering algorithms and competitive neural network. A self-estimation algorithm was developed to determine the

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number of clusters. The images segmented by using these techniques were compared by making use of peak signal to noise ratio and compression ratio. Sandeep Chaplot et al. [16] proposed a novel method using wavelets as input to self organising map neural network and Support Vector Machine for the classification of magnetic resonance brain images. Good classification accuracy was achieved for Support Vector Machine classifier. EI-Sayed *et al.* [17] surveyed a new algorithm by following the computational methods using feedback pulse-coupled neural network for image segmentation, discrete wavelet transform for feature extraction, principal component analysis for dimentionality reduction and feed forward back propogation neural network to classify the image as normal or abnormal. A. Rajendran *et al.* [18] proposed a method to combine region based fuzzy clustering with deformable model for segmenting tumor region on MRI images. Region based fuzzy clustering technique was used for initial segmentation of tumor, the result of this method was used to provide initial contour for deformable model which then determines the final contour to extract tumor boundary for final segmentation. EI-Sayed Ahmed *et al.* [19] proposed hybrid technique including discrete wavelet transform for feature extraction, principal component analysis for feature reduction, feed forward back propogation artificial neural network and K- nearest neighbour classifiers to classify the images as normal or abnormal. N. Abdullah *et al.* [20] applied Support Vector Machine technique for the classification of brain magnetic resonance image. Sadik Kara *et al.* [21] discussed about discrete wavelet transform of Doppler signals acquired from carotid arteries with atherosclerosis patients, principal component analysis for data reduction and artificial neural network classifier to distinguish between atherosclerosis and healthy subjects. Nelly Gordillo et al. [22] presented an overview of the most relevant brain tumor segmentation methods. The semi automatic and fully automatic techniques were discussed. Quratul Ain *et al.* [23] proposed an automatic diagnosis system for the detection of brain tumor. In this, textural features were extracted from the noise free brain MR images and the ensemble based Support Vector Machine classification was used. R. M. Haralick et al. [24] reviewed about the textural features for image classification. F. Latifoglu *et al.* [25] discussed about the diagnosis of atherosclerosis rom carotid artery doppler signals by using principal component analysis for dimension reduction, k-nearest neighbour based pre-processing and Artificial immune recognition system. C.Burges [26] presented a Tutorial on support vector machine for pattern recognition. In this proposed method the features are extracted through gray level co-occurrence matrix method and a supervised technique such as support vector machine has been selected for classification and its performance was analysed and compared.

2. PROPOSED WORK

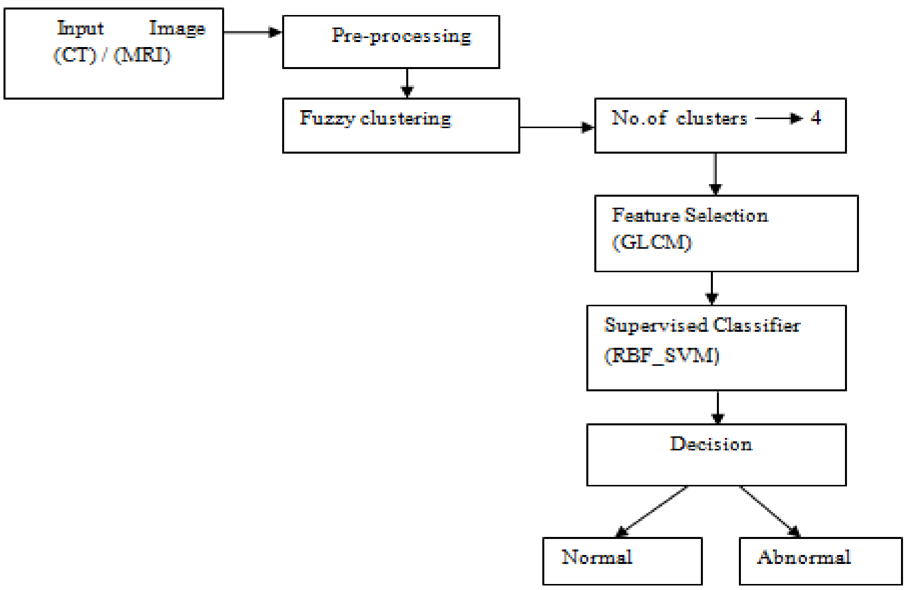

Figure-1. Schematic diagram of the proposed work.

In the proposed method, as shown in figure 1, the input images were pre-processed by using median filter. In order to extract the region of interest the fuzzy clustering technique was applied over the input images. The input image has been divided into 4 clusters. Here, the fuzzy c-means clustering technique has been preferred since; fuzzy c-means clustering is mainly preferred for medical images only to reduce the partial volume effect [27]. Gray Level Co- occurrence Matrix method was used for extracting the features from each cluster of the brain portion and also from CT liver images. Then the images were classified as normal and abnormal. With these observed features the performance of the supervised classifier has been analysed and compared.

A. Fuzzy clustering

Fuzzy clustering plays an important role in image segmentation. In fuzzy clustering, fuzzy c-means algorithm is an effective algorithm. The standard fuzzy c-means' objective function is given by,

$$J_{fcm} = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \left\| x_j - c_i \right\|^2 \tag{1}$$

where 'c' is the number of clusters; 'c_i' is the cluster center; and 'm' is the weighing exponent. The updation of membership (u_{ij}) and cluster center (c_i) is given by,

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\left\| x_j - c_i \right\|}{\left\| x_j - c_k \right\|} \right)^{\frac{2}{(m-1)}}} \tag{2}$$

$$c_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} x_j}{\sum_{j=1}^{n} u_{ij}^{m}} \tag{3}$$

B. Features selection

In this approach the features are extracted using GLCM method. The co-occurrence matrix is a statistical method used to extract the second order statistical textural features from the given image. In GLCM the number of rows and columns is equal to the number of gray levels [28, 29]. The first order histogram based features are extracted using the formulae given below [30]. In this proposed method shape, textural and statistical features are extracted from each cluster and given to the classifier to find the abnormalities in the given image. The extracted features are [2],

$$\text{Entropy} = \sum_{i=0}^{ng-1} \sum_{j=0}^{ng-1} - p_{ij} \log p_{ij} \tag{4}$$

Entropy is defined as a measure of uncertainty in a random variable. Its value will be maximum when all the elements of the co-occurrence matrix are the same.

$$\text{Correlation} = \frac{\sum_{i=0}^{ng-1} \sum_{j=0}^{ng-1} (i, j) p(i, j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{5}$$

Correlation measures, how the reference pixel is related to its neighbor pixel.

$$\text{Energy} = \sum_{i=0}^{ng-1} \sum_{j=0}^{ng-1} p_{ij}^2 \tag{6}$$

Energy defines the measure of sum of squared elements. This measures the homogeneity. When pixels are very similar, the energy value will be large.

$$\text{Contrast} = \sum_{n=0}^{ng-1} n^2 \sum_{i=0}^{ng-1} \sum_{j=0}^{ng-1} p(i.j)^2 \tag{7}$$

Contrast measures the intensity variation between the reference pixel and neighbor pixel.

$$\text{Mean } (\mu) = \sum_{i=0}^{ng-1} i.p(i) \tag{8}$$

The mean defines the average level of intensity of the image or texture.

$$\text{Standard deviation } (\sigma) = \sqrt{\sum_{i=0}^{ng-1} (i-\mu)^2 .p(i)} \tag{9}$$

$$\text{Variance } (\sigma^2) = \sum_{i=0}^{ng-1} (i-\mu)^2 .p(i) \tag{10}$$

The variance defines the variation of intensity around the mean.

3. CLASSIFIER

Support vector machine is a linear machine developed from statistical learning theory and used in many fields like bio-informatics, image recognition, pattern classification etc. The objective of Support Vector Machine is to construct a hyperplane as the decision surface in such a way that the margin of separation between positive and negative support vectors is maximized. In the proposed method RBF-SVM is used for classification process to identify whether the given image is normal or abnormal. Radial basis kernel function maps the linear data space into non-linear feature space. Radial basis functions utilize the combination of supervised and un supervised learning techniques. This approach can be used for modelling and classification. It can also be used for dimentionality reduction.

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4. RESULTS AND DISCUSSIONS

The MR brain images have been collected from the Department of Radiology, Medical College and Hospital (RMMCH), Annamalai University. The images are T1 and T2 weighted with the thickness of 1mm and size 512 X 512 each. At first, the image was converted into gray scale image. It was pre-processed by a median filter. The standard fuzzy c-means clustering technique is applied over the image to form the clusters. The shape, texture and statistical features are extracted from the region of interest with help of gray level co- occurrence matrix method. The features are given to supervised RBF-SVM classifier to classify the images as normal and abnormal. Figures 2 and 6 show the accurate diagnosis of tumor in MR brain images. Figures 3 & 7 give the details of the formation of clusters of the respective images.

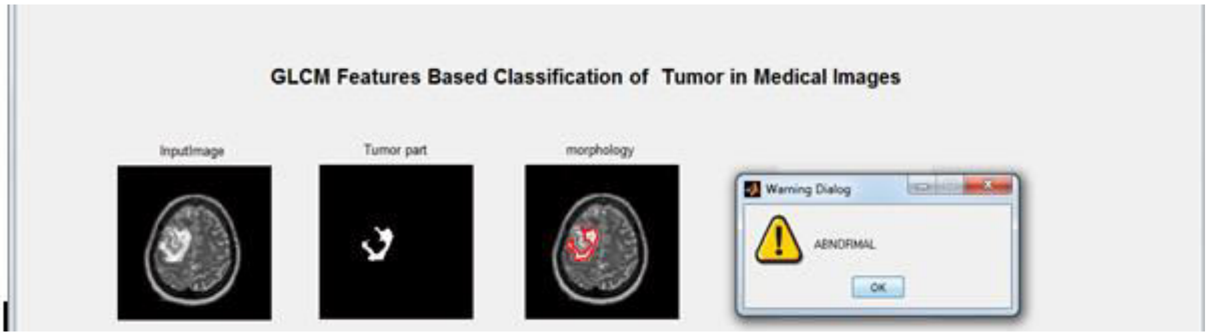

Figure-2. Perfect prediction of the proposed classifier for MRI brain image.

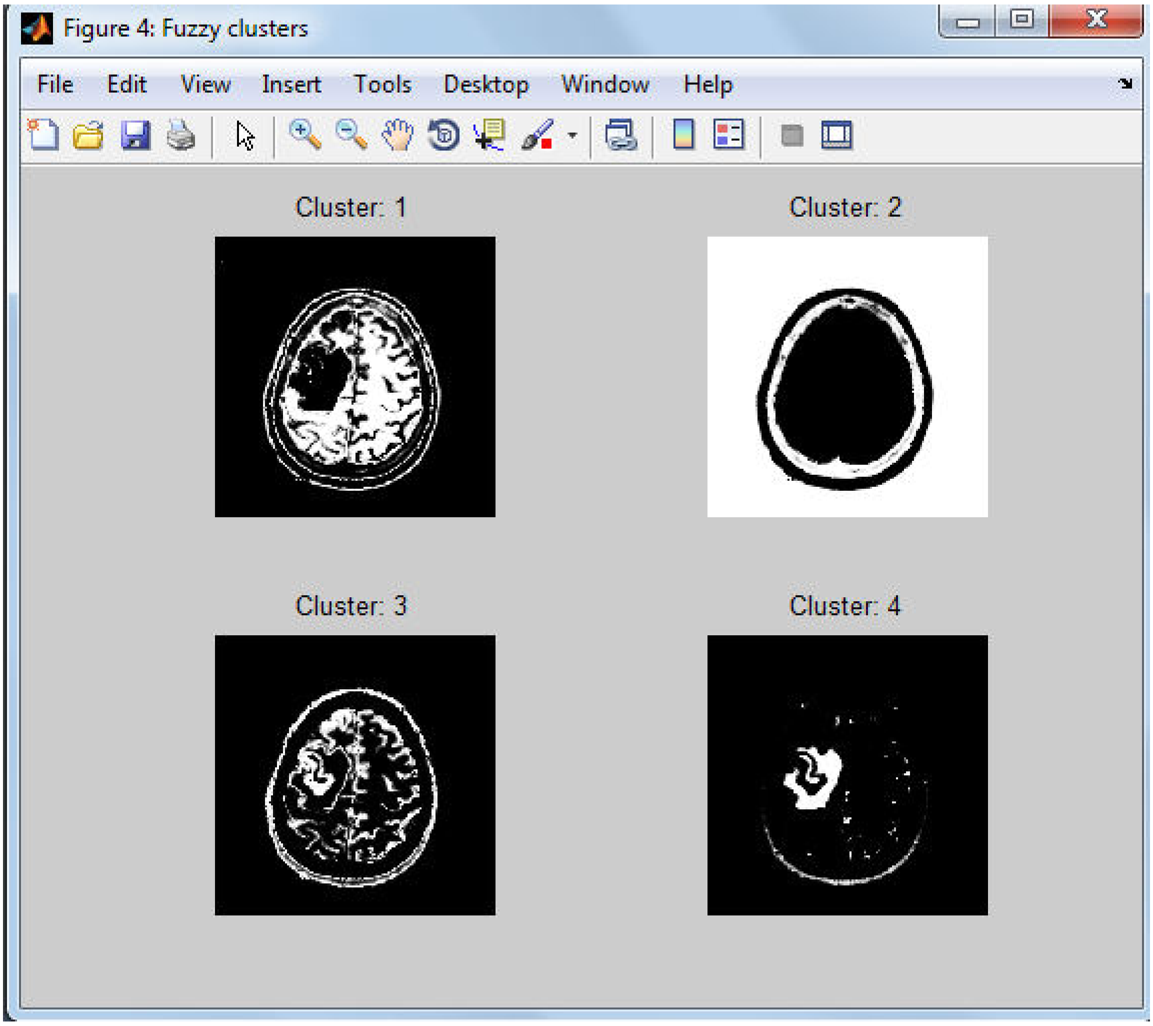

Figure-3. Cluster formation for the above MRI brain image.

Figure-4 depicts the correct decision made by the classifier for normal case. Figure-5. represents the cluster formation of the same.

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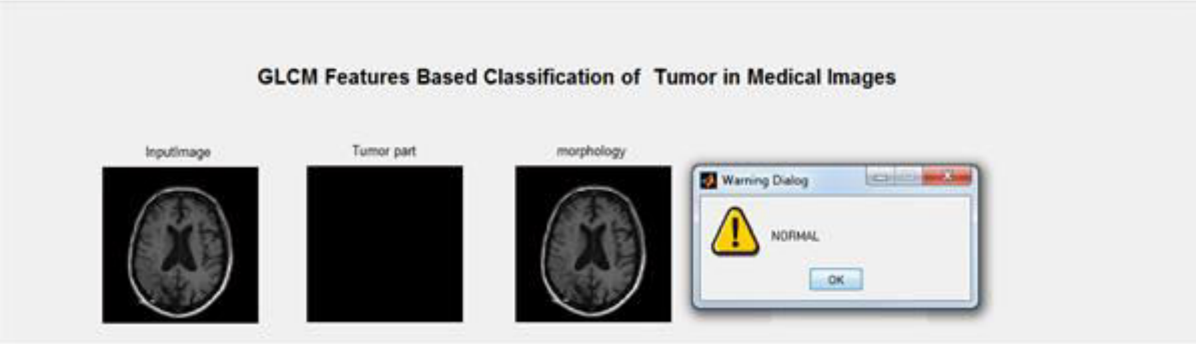

Figure-4. Perfect prediction of the proposed classifier for MRI brain image.

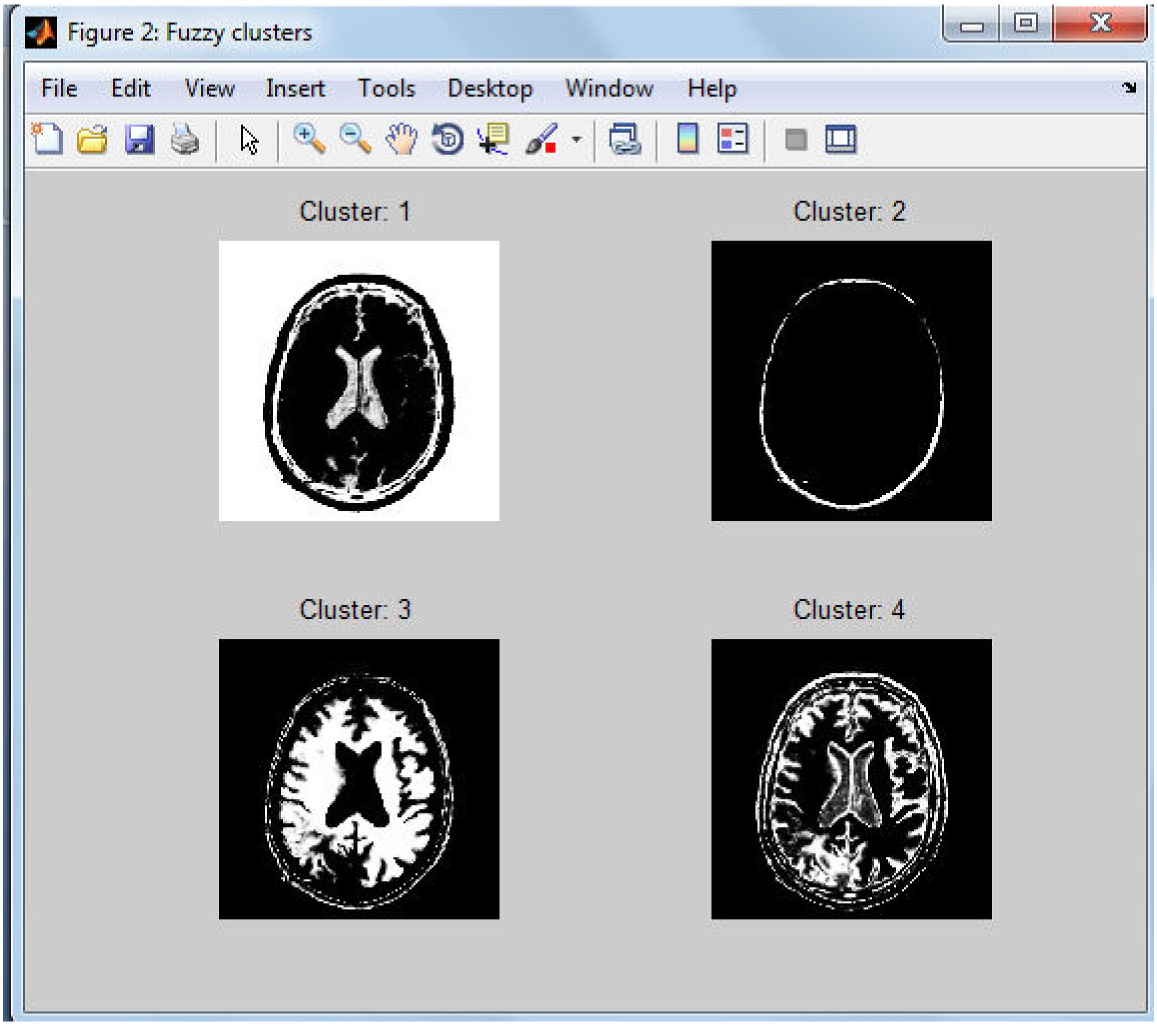

Figure-5. Cluster formation for the above MRI brain image.

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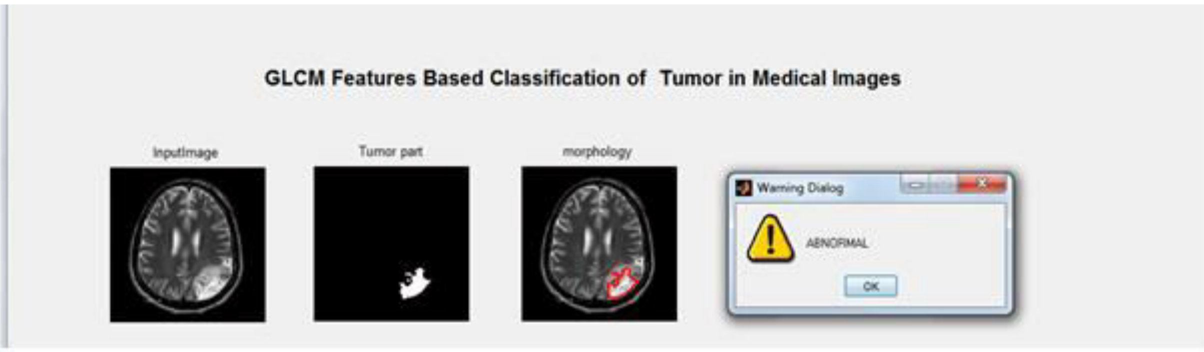

Figure-6. Perfect prediction of the proposed classifier for MRI brain image.

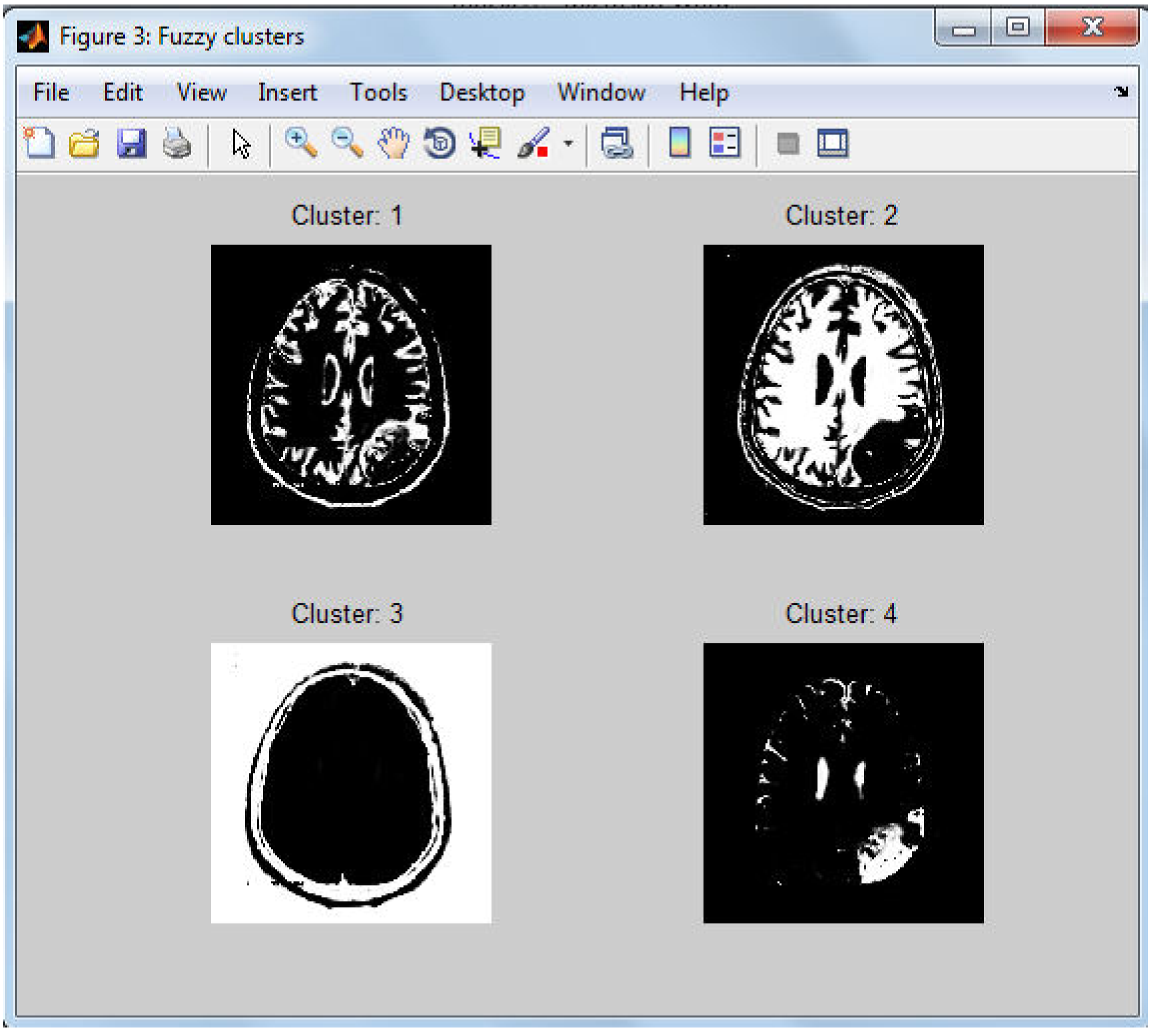

Figure-7. Cluster formation for the above MRI brain image.

Figure-8 explains the perfect prediction of the classifier for abnormal case in CT liver image. Figure-9 gives the details about its clusters.

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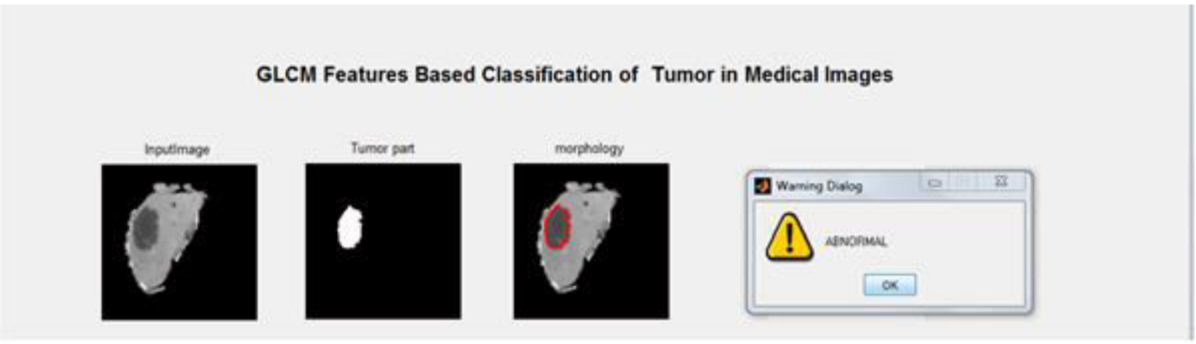

Figure-8. Perfect prediction of the proposed classifier for CT Liver image.

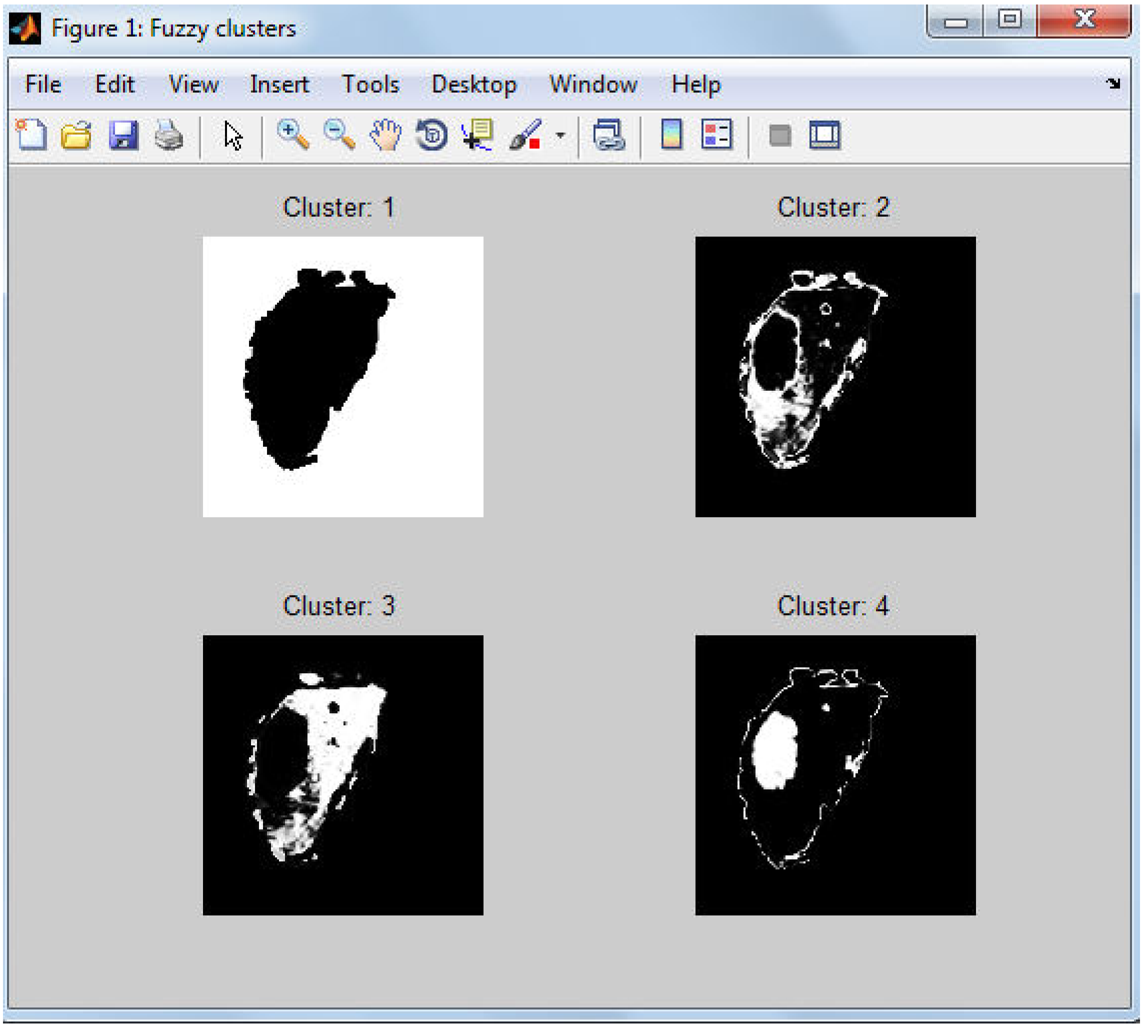

Figure-9. Cluster formation for the above CT Liver image.

Figure-10 is for the detection of normal case in CT liver image. Figure-11 describes the formation of its clusters.

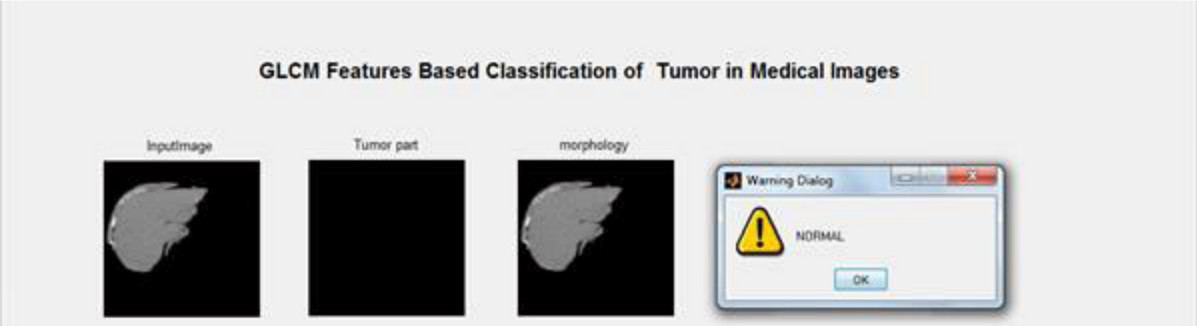

Figure-10. Perfect prediction of the proposed classifier for CT Liver image.

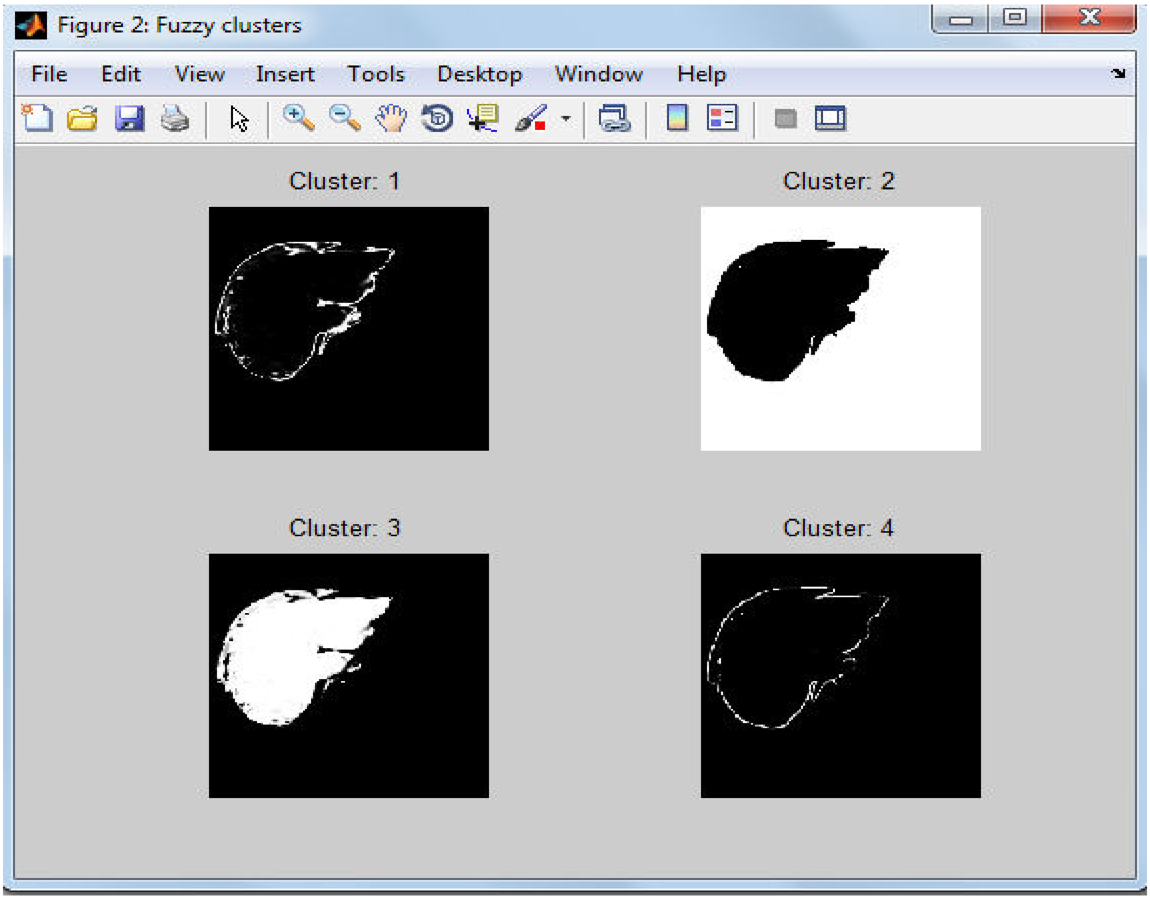

Figure-11. Cluster formation of the above CT Liver image.

Table-1 describes the features for normal brain images. Table-2 depicts the features for normal liver images. Table-3 shows the features for abnormal brain images. Table-4 gives the details for abnormal liver images.

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Table-1. Features for normal brain images.

Area	Perimeter	Contrast	Correlation	Energy	Entropy	Mean	Std.dev	Variance
28510	57018	1.0951	0.67164	0.13433	2.5246	0.2896	0.16337	0.02669
25224	50446	0.85505	0.77256	0.093374	2.7689	0.30172	0.17514	0.030674
1.47E+05	2.93E+05	0.68575	0.85992	0.12157	2.6457	0.28673	0.20064	0.040258
1.45E+05	2.89E+05	0.59655	0.88091	0.12595	2.5921	0.28642	0.20246	0.04099
32284	64566	1.2336	0.63412	0.12823	2.5847	0.29937	0.16654	0.027735
31820	63638	1.1896	0.64111	0.11379	2.6655	0.30659	0.16618	0.027616
32996	65990	0.79166	0.89269	0.12412	2.6287	0.47856	0.25052	0.062762
30560	61118	0.871	0.91402	0.080613	2.9571	0.49778	0.29123	0.084817
34139	68276	1.1961	0.63889	0.18789	2.3729	0.2844	0.16427	0.026985
75482	1.51E+05	0.32011	0.87378	0.15698	2.2024	0.4033	0.13693	0.01875

Table-2. Features for normal liver images.

Area	Perimeter	Contrast	Correlation	Energy	Entropy	Mean	Std.dev	Variance
76481	1.53E+05	0.1903	0.89213	0.26387	1.7956	0.35464	0.12169	0.014807
28278	56554	1.0911	0.69051	0.14012	2.5199	0.30815	0.17115	0.029293
60084	1.20E+05	0.50105	0.8359	0.19848	2.2571	0.31313	0.15689	0.024616
27887	55772	1.3234	0.84868	0.070212	3.1575	0.42088	0.27275	0.074395
37688	75374	0.71114	0.89	0.11367	2.7546	0.62075	0.22983	0.052822
22579	45156	1.9764	0.734	0.05452	3.3312	0.62838	0.24999	0.062496
27430	54858	1.0339	0.71074	0.14909	2.4885	0.30955	0.17069	0.029136
23540	47078	1.1711	0.67074	0.10354	2.7765	0.26114	0.17212	0.029624
22343	44684	1.4216	0.66522	0.080633	3.0372	0.32699	0.18662	0.034826
37062	74122	0.89099	0.67111	0.17634	2.4047	0.28327	0.14886	0.022161

Table-3. Features for abnormal brain images.

Area	Perimeter	Contrast	Correlation	Energy	Entropy	Mean	Std.dev	Variance
29829	59656	0.82583	0.91277	0.09358	2.8531	0.47804	0.28153	0.079257
98683	1.97E+05	0.51278	0.91065	0.094025	2.7939	0.3628	0.21394	0.045769
1.34E+05	2.68E+05	0.50149	0.90111	0.11798	2.6354	0.30471	0.2011	0.04044
3.43E+05	6.86E+05	0.3608	0.93807	0.14076	2.503	0.38991	0.22587	0.051018
53268	1.07E+05	0.43818	0.92424	0.29116	1.9875	0.16773	0.23057	0.053164
3.43E+05	6.86E+05	0.3608	0.93807	0.14076	2.503	0.38991	0.22587	0.051018
37978	75954	0.77428	0.86399	0.23532	2.2396	0.22253	0.22432	0.050319
66871	1.34E+05	0.57393	0.79896	0.28058	1.6271	0.34439	0.14472	0.020944
3.43E+05	6.86E+05	0.3608	0.93807	0.14076	2.503	0.38991	0.22587	0.051018
65536	1.31E+05	0.30451	0.92679	0.32596	1.8334	0.18743	0.18601	0.034601

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Table-4. Features for abnormal liver images.

Area	Perimeter	Contrast	Correlation	Energy	Entropy	Mean	Std.dev	Variance
1.17E+05	2.33E+05	0.6155	0.91832	0.077933	2.9475	0.36672	0.24598	0.060507
53268	1.07E+05	0.43818	0.92424	0.29116	1.9875	0.16773	0.23057	0.053164
1.12E+05	2.23E+05	0.47761	0.92072	0.11162	2.7043	0.36638	0.22115	0.048908
37978	75954	0.77428	0.86399	0.23532	2.2396	0.22253	0.22432	0.050319
66871	1.34E+05	0.57393	0.79896	0.28058	1.6271	0.34439	0.14472	0.020944
1.05E+05	2.09E+05	0.59012	0.91833	0.073377	2.9694	0.37011	0.24046	0.05782
1.45E+05	2.89E+05	0.69414	0.88	0.10304	2.7993	0.31899	0.21696	0.04707
1.34E+05	2.68E+05	0.50065	0.90112	0.11736	2.6395	0.30516	0.20081	0.040326
31348	62694	0.94653	0.73221	0.16118	2.4133	0.24463	0.16794	0.028205
25300	50598	0.8343	0.82729	0.10377	2.7521	0.27179	0.19336	0.037388

Totally 70 normal cases and 60 abnormal cases were analysed. It has been found from the Table 1- 4 that the correlation level is form 0.6 – 0.9, the entropy range is from 1.9 - 3.1 and the contrast value is around 1 which will enable the proposed classifier system to classify the nature of tissue with high accuracy. The accuracy of the classifier was evaluated based on the error rate. The error rate was calculated using the terms true positive (TP), true negative (TN), false positive (FP) and false negative (FN). Sensitivity and Specificity are the statistical measures used to analyse the performance of the classifier.

True Positive (TP) - Abnormal cases correctly classified.

True Negative (TN) - Normal cases correctly classified.

False Positive (FP) - Normal cases classified as abnormal.

False Negative (FN) - Abnormal cases classified as normal.

Sensitivity represents the capability of the system to diagnose the abnormal cases correctly. Specificity represents the capability of the system to diagnose the normal cases correctly.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \tag{11}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{12}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{13}$$

Table-5. Performance evaluation of classifier.

S. No.	Classification techniques	True positive	True negative	False positive	False negative	Sensitivity	Specificity	Accuracy In %
1.	Multi-RBF SVM	58	69	1	2	0.966	0.985	98

Total no. of normal cases 70. Total no.of abnormal cases 60.

Table-5 shows the Performance analysis of the classifier used. From table 5 it is seen that the proposed RBF-SVM classifier can able to detect 58 abnormal cases and 69 normal cases correctly with the accuracy of around 98%. The performance of the classifier was compared with other types of classifiers the results are given in Table-6.

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Table-6. Comparative analysis of classifier performance.

Classification techniques used	Performance accuracy in %
DWT + SOM [16]	94
DWT + SVM with Linear Kernel [16]	96
DWT + PCA + ANN [19]	97
GLCM Features + CPN [30]	92.5
GLCM features + MKNN [30]	95
Proposed GLCM + RBF- SVM	98

From Table-5 and from the Figures 2-10 it has been concluded that our proposed RBF-SVM classifier is found to be good for the detection of abnormalities in medical images.

5. CONCLUSIONS

In this paper, the performance of the supervised classification technique for the detection of abnormalities in magnetic resonance brain images and computed tomography liver images has been discussed. Totally 130 patients have been taken in to consideration. Among those 70 patients were in normal condition and 60 patients were in abnormal condition. The RBF-support vector machine classifier correctly identifies 69 normal cases and 58 abnormal cases with the accuracy of around 98% through Fuzzy clustering and GLCM based feature selection techniques. The performance of the proposed classifier has been analysed and compared with the other existing classifier techniques, it has been concluded that the RBF-SVM classifier is best suited for the classification of brain magnetic resonance images and computed tomography liver images correctly. Future work will focus on the selection of features based on evolutionary algorithms.

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