AUTOMATIC BRAIN TUMOR SEGMENTATION AND CLASSIFICATION

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Abstract: In this paper the work is to reduce the physician time by assessing with computer aided tumor detection. Human investigation is the routine technique for brain MRI tumour detection and tumors classification. The proposed system classifies the brain tumors in double training process which gives preferable performance over the traditional classification method. The proposed SVM classifier can accurately classifying the status of the brain image into normal / abnormal and KNN classifier can classify the grades of tumor.

IndexTerms - MRI, KNN, CNN.

I. INTRODUCTION

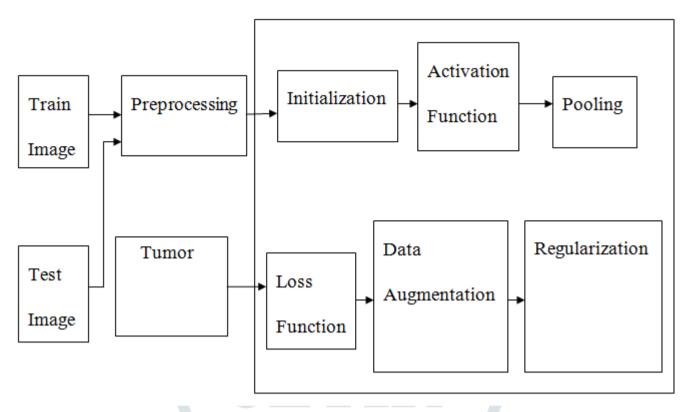
The brain tumor identification is very sensitive process because of its complicate structure by nature. The tumor parts area is having unequal structure from one patient to another. In order to segment the tumor part, first the brain is to be classified / checked out whether it is having tumor part or not. This computer aided Diagnosis may help the physicians who may struggle with the small tumor part.

It is one form of signal processing technique in which the input can be an image like photograph or video frame and the output of the process is either an image or a set of characteristics related to the image. Usually in image-processing technique the images will be treated as a two-dimensional signal and to their standard signal-processing technique will be applied. In general image processing techniques are referred as digital process, but nowadays optical and analog image processing modes is possible. In simple acquisition of image is referred as imaging. In animated movies the computer graphic images are manually made from physical models like objects, environments and lighting, instead of being acquired from natural scenes. Computer vision is often considered as a high-level image processing out of which, a machine/computer/software intends to decipher the physical contents of an image or a sequence of images.

II. EXISTING SYSTEM

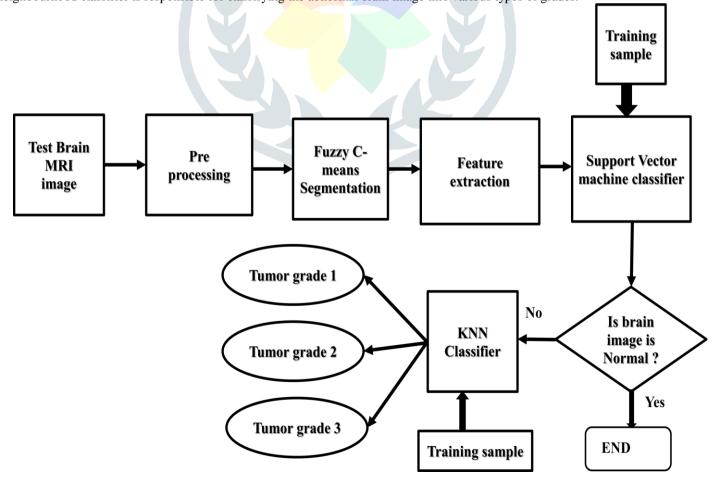
There are many method used for segmenting brain tumor but using convolutional neural network the segmentation can be more reliable when compared to other methods Convolutional Neural Network has 3 layers input layer, hidden layer, output layer. In machine learning, a CNN, or Convolutional Neural Network is a type of feed-forward artificial neural network in which the connectivity pattern between its neurons is inspired by the organization of the animal visual cortex, whose individual neurons are arranged in such a way that they respond to overlapping regions tiling the visual field. Convolutional Network where inspired by biological processes.

Here two images are given as input image there are the train and test image. The images are pre-processed and then they are passed in to a series of layers in convolutional neural network. It consists of 6 convolutional layers, 2 max pooling layers and 3 fully connected layers.



III. PROPOSED SYSTEM

This section elucidates the system design and methodology which concerns its ultimate design and the features of proposed system. The overall system design of the proposed method is illustrated in below Figure. The proposed work starts with the acquisition of brain MRI images of both normal and abnormal cases. The pre-processing techniques will help to improve the brain image quality and adaptive segmentation technique is useful to segment the brain portion separately. The GLCM (Gray level Covariance Matrix) features are extracted from the images it is used to train the SOM (Self Organized mapping) trainer. The Support Vector Machine Classifier is responsible to classify the test brain image into normal / abnormal. Finally the K-nearest neighbourhood classifier is responsible for classifying the abnormal brain image into various types of grades.



IV. RESULTS AND DISCUSSION

TEST IMAGES

The proposed system is implemented using a MATLAB 2014a. The algorithm is tested on a BRAINX database of 397 images where it is evaluated for brain tumor detection. These images are the most widely used standard test images used for image retargeting algorithms. The images contains a nice mixture of detail, flat regions, shading and texture that do a good job of testing various image processing algorithms. These images are used for many image processing researches.

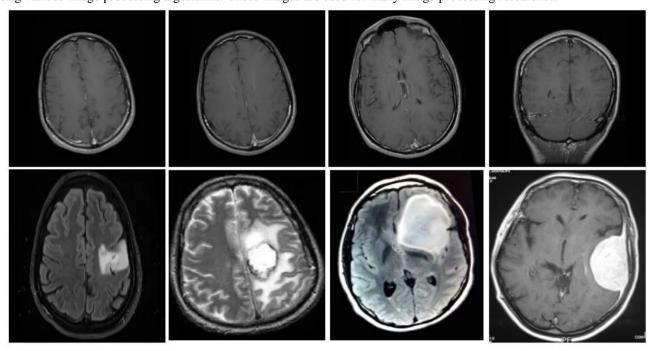


Figure 4.1 Test images (Top row: normal images & Bottom row: Abnormal images)

Simulation results

This section elaborates the results obtained for the proposed work and the proposed work is implemented on MATLAB GUI shown in below figures.

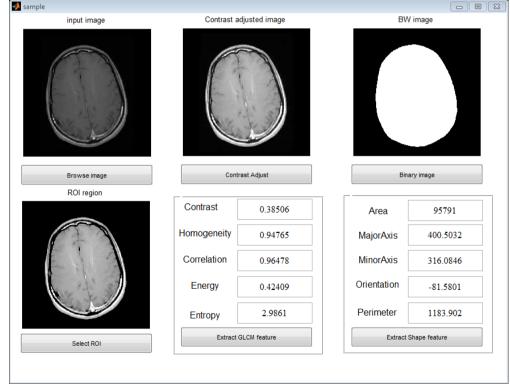


Figure 4.2 GUI for Pre-processing

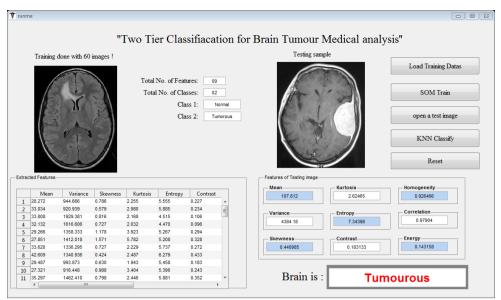


Figure 4.3 GUI for Two-Tier classification

Table 4.1 Feature matrix of 30 samples

The following table 4.1 presenting the features distribution of normal and tumorous images in this proposed work.

Mean Variance Skewness Kurtosis **Entropy** Contrast Homogeneity Correlation Energy Class 28.272 'Normal' 944.666 2.255 5.555 0.2270.9270.846 0.394 0.786'Normal' 33.034 920.939 0.579 2.980 5.885 0.234 0.908 0.841 0.297 4.515 33.808 1929.381 0.816 2.168 0.106 0.961 0.961 0.434 'Normal' 2.032 'Normal' 32.132 1616.606 0.727 4.470 0.096 0.965 0.955 0.455 29.266 1358.333 1.178 3.923 5.267 0.294 0.923 0.857 0.421 'Normal' 27.851 5.782 0.917 'Normal' 1412.018 1.571 5.208 0.328 0.850 0.425 1336.295 33.620 0.727 2.229 5.737 0.272 0.918 0.863 0.384 'Normal' 0.795'Normal' 42.609 1340.936 0.424 2.487 6.279 0.433 0.872 0.248 29.487 993.873 0.630 1.943 5.458 0.932 0.388 'Normal' 0.183 0.88027.321 3.404 5.390 0.2430.918 0.832 0.385 'Normal' 916.448 0.988 35.297 2.446 'Normal' 1462.410 0.798 5.881 0.352 0.900 0.844 0.364 28.293 958.065 0.658 2.063 5.277 0.180 0.929 0.878 0.395 'Normal' 48.071 1753.907 0.306 1.627 6.493 0.500 0.854 0.8290.226 'Normal' 40.194 1876.106 0.439 'Normal' 1.767 4.954 0.1220.9570.950 0.396 40.927 2120.652 0.933 3.424 5.362 0.167 0.941 0.949 0.350 'Normal' 94.381 7571.237 0.348 1.681 6.474 0.101 0.962 0.992 0.210 'Tumourous' 'Tumourous' 81.480 2329.093 1.466 5.472 7.030 0.624 0.835 0.855 0.158 42.580 4032.427 1.377 4.201 3.829 0.523 0.922 0.916 0.424 'Tumourous' 111.576 3092.035 3.455 7.270 1.173 0.727 0.795 0.080 'Tumourous' 0.665 4.974 0.939 33.831 1488.382 1.337 5.826 0.161 0.933 0.372 'Tumourous' 47.794 2249.904 3.780 5.788 0.307 0.892 0.926 0.322 'Tumourous' 1.115 106.833 0.449 3799.902 2.765 7.009 0.813 0.838 0.895 0.113 'Tumourous' 47.195 1993.966 0.414 2.355 5.026 0.102 0.956 0.965 0.331 'Tumourous' 0.884 'Tumourous' 66.914 2813.037 0.642 3.342 6.577 0.427 0.911 0.18677.158 4618.765 0.582 2.758 6.716 0.424 0.892 0.945 0.192 'Tumourous' 2253.671 66.263 5.193 6.538 0.194 0.932 0.961 0.231 'Tumourous' 1.264 4.376 5.785 58.641 5431.423 1.515 0.306 0.928 0.965 0.252 'Tumourous' 94.856 4638.290 0.393 2.651 7.181 0.637 0.873 0.923 0.145 'Tumourous'

The boundary labelled image is shown in the following figure where the clustering is done with the help of fuzzy C-means algorithm. The boundary pixels are labelled as red colour in the following figure 4.4

0.522

0.509

0.853

0.904

0.922

0.935

0.132

0.206

89.755

82.454

3480.795

4842.053

0.312

0.545

2.511

2.917

6.329

6.016

Tumourous'

'Tumourous'

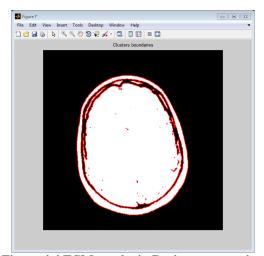


Figure 4.4 FCM results in Brain segmentation

The segmented brain portion is shown in the following figure 4.5 where this binary image is used for the shape feature extraction and the gray image is used for texture feature extraction.

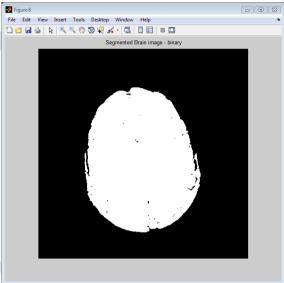


Figure 4.5 Segmented Brain binary image

The brain binary image is multiplied with the gray image and the resultant gray segmented image is shown in the following figure 4.6.

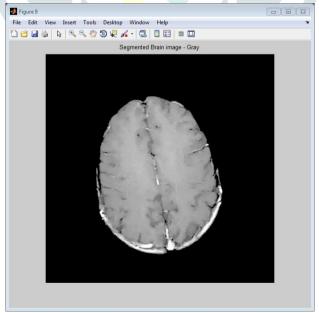


Figure 4.6 Segmented Brain binary image

The extracted features such as shape and texture features are shown in the following table 4.2

Performance evaluation

The proposed work is achieving the maximum accuracy level as 96.667% and the also obtaining the maximum recognition rate for this two tier classifier work. This section elaborates the performance of the proposed system in detail.

Performance measure procedure was done by comparing the segmentation results to the reference image. There are four values resulted from the validation procedure, true positive (TP), false positive (FP), true negative (TN) and false negative (FN). True positives is a number of images correctly detected as normal, false positive is a number of images incorrectly flagged, true negatives is a number of images correctly detected as tumor image and false negative (FN) is a number of image incorrectly flagged as tumor.

Table 4.2 Performance Parameters

Table 4.21 citormance I arameters						
	Normal	Tumorous				
Detected	True positive	False positive				
	(TP)	(FP)				
Not detected	False Negative	True Negative				
	(FN)	(TN)				

For evaluation purpose, all the parameters are determined for each image in the data set. Sensitivity, Specificity and Predictivity are used as accuracy measures.

Sensitivity

It is the probability that a test result will be positive when the selected mage is normal. It is defined as the ratio between True positive (TP) and addition of True positive (TP) and False negative (FN).

Sensitivity =
$$\frac{TP}{(TP + FN)}$$

Specificity

It is the probability that a test result will be negative when the selected image is tumor. It is defined as the ratio between True negative (TN) and addition of False positive (FP) and True negative (TN).

Specificity =
$$\frac{TN}{(FP + TN)}$$

Predictivity

It is the probability that the tumor is present when the detected while tracing.

It is defined as the ratio between True positive (TP) and addition of True positive (TP) and False positive (FP).

$$\frac{Predictivity}{(TP + FP)}$$

Performance Results of brain tumor classification

The above parameters are measured for the six sample images and tabulated in Table 4.3

Table 4.3 Parameter of obtained results

Tuble the Lunderer of obtaining results					
Parameters Parameters Parameters	Value				
Accuracy	96.667				
Error rate	3.333				
Sensitivity	96.667				
Specificity	0.9667				
Positive Predictive Value	0.9667				
Negative Predictive Value	0.9667				
Prevalence	0.5				
	Parameters Accuracy Error rate Sensitivity Specificity Positive Predictive Value Negative Predictive Value				

The following table 4.4 represents the confusion matrix obtained for the proposed work

Table 4.4 Confusion matrix for the obtained results

Table 4.4 Comusion matrix for the obtained results						
	Normal	Tumorous				
Detected	29	1				
	(TP)	(FP)				
Not detected	1	29				
	(FN)	(TN)				

The following figure 4.7 represents the ROC curve for the proposed work where the TPR is maximum that indicates about the maximum recognition rate of the proposed two tier classifier

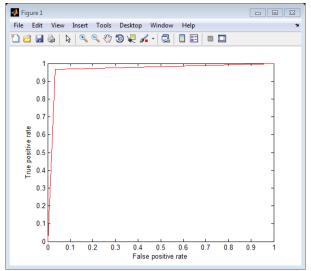
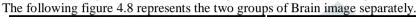


Figure 4.7 ROC for the proposed work

The Brain tumor grade classification is implemented on 20 MR images where the grades obtained are Benign and Malignant.



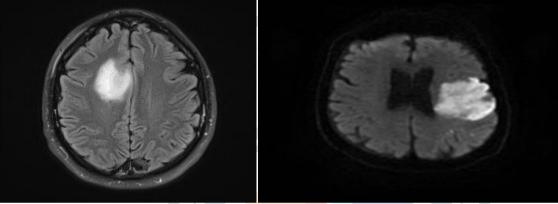


Figure 4.8 Two different grades of brain tumor (a) Benign tumor (b) malignant tumor

The features extracted from the test image are tabulated in the following table 4.5. Where the texture and shape features are preferred for the analysis.

Table 4.5 Features from two grades of MRI

	Table 4.5 Features from two grades of MRI										
	Texture features					Shape features				Grade	
S.No	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	
1	0.51	0.22	0.91	0.98	0.91	7969.00	154.33	96.06	0.82	1169.24	1
									-		
2	2.78	0.35	0.94	0.92	0.48	19883.00	182.23	142.11	88.37	877.96	1
3	4.71	0.66	0.94	0.86	0.23	25955.00	206.42	166.47	- 79.94	961.12	1
											1
4	5.28	0.27	0.97	0.93	0.23	78223.00	355.11	301.72	87.52	2940.92	1
5	3.36	0.27	0.96	0.93	0.42	95117.00	398.83	306.89	87.46	1972.24	1
6	4.99	2.38	0.79	0.83	0.19	11111.00	141.34	113.02	86.29	396.57	1
									-		
7	2.63	0.22	0.97	0.95	0.53	17819.00	159.80	148.54	60.51	634.81	1
									-		
8	2.51	0.50	0.93	0.91	0.49	18403.00	196.76	150.81	83.45	1444.42	1
									-		
9	2.69	0.69	0.92	0.90	0.52	10853.00	138.02	106.22	89.29	475.62	1
									-		
10	3.80	0.52	0.92	0.91	0.32	33283.00	252.92	215.79	77.25	1454.97	2
									-		
11	3.28	0.22	0.95	0.94	0.40	162506.00	532.32	512.57	84.00	3970.30	2
12	2.80	0.12	0.96	0.96	0.48	138072.00	511.91	426.52	83.08	4985.53	2
									-		
13	3.66	0.22	0.98	0.95	0.31	157847.00	520.32	409.40	81.29	2888.23	2
14	4.37	0.20	0.96	0.94	0.29	94663.00	423.26	297.02	88.98	1325.20	2
15	3.74	0.32	0.91	0.88	0.30	33376.00	213.21	207.15	47.24	1298.66	2
									-		
16	2.21	0.16	0.96	0.95	0.58	15394.00	167.15	149.97	65.03	746.26	2
17	1.02	0.21	0.97	0.98	0.80	6560.00	118.21	79.95	81.50	509.24	2

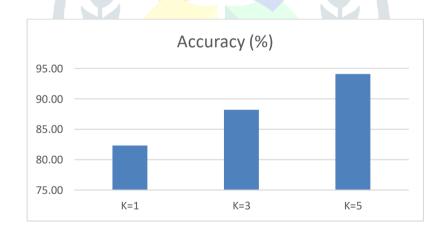
F1 – entropy; F2 – Contrast; F3 – Correlation; F4 – Homogeneity; F5 – Energy; F6 – Area; F7 – Major axis; F8 – Minor axis; F9 – Orientation; F10 – Perimeter

Grade 1 – Benign class; Grade 2 – Malignant class.

The KNN classifier is applied for the purpose of grade classification where the result achieved maximum response in terms of different various 'K' values. The following table represents the results obtained from the KNN classifier.

KNN classification S.No **Original class** K=1 K=3 K=5 Benign Benign Benign Benign 1 2 Benign Benign Benign Benign 3 Benign Malignant Malignant Benign 4 Benign Benign Benign Benign 5 Benign Benign Benign Benign 6 Benign Benign Benign Benign 7 Benign Malignant Benign Benign 8 Benign Benign Benign Benign 9 Benign Benign Benign Benign 10 Malignant Malignant Malignant Malignant 11 Malignant Malignant Malignant Malignant 12 Malignant Malignant Malignant Malignant 13 Malignant Malignant Malignant Malignant 14 Malignant Benign Benign Malignant 15 Malignant Malignant Malignant Malignant Malignant Malignant Malignant 16 Malignant 17 Malignant Benign Malignant Malignant Accuracy= 82.35 % 88,235 % 94.11 Correctly classified / total samples

Table 4.6 Results from KNN classifier



This proposed work achieved maximum accuracy as 94.11% in grade classification with the help KNN classification. Thus the system is fully automatic doesn't required any human intervention

V. CONCLUSION AND FUTURE SCOPE CONCLUSION

This proposed work genesis an efficient recognition system for the brain tumor classification and the by not focusing on the traditional way, this work travels on two tier classification method. This work presented for totally 60 images of both normal and abnormal images and MATLAB image processing toolbox is useful for developing the proposed work. Firstly the brain MRI images are pre-processed because it is well-known to everyone about the noises present in the MRI images. The pre-processed images are undergone for the Fuzzy C means segmentation where the brain ROI extracted precisely. The feature extraction is done by processing tithe GLC matrix and the shape and texture features are collected for every image. The collected features vectors are trained the KNN classifier where the variance among the feature set is increased tightly and making the classifier learning rate as high. The K-NN classifier is effectively classifying the images very accurately and the also it assures maximum accuracy as 96.7%.

FUTURE WORK

This proposed work is focusing the traditional parametric feature extraction technique for this recognition task. The future work may be extended this feature extraction process in terms of deep learning neural network. Convolutional neural networks are the most delicate network for the field of image processing and also the algorithm need to be extended for segmenting the tumorous area.

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