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MRI Brain Tumour Image Retrieval Using Low Level Features and High Level Semantics

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Abstract

Content Based Image Retrieval (CBIR) is automatic retrieval of similar images based on shape, texture, colour and other features. It has wide applications in search, indexing, finding similar images, training and research. Various works are on CBIR are found to be effective on colour images based on colour features. Retrieving similar medical images is found to be difficult task due to the grey colour properties of medical images and extracting various effective features for discriminating tumours. In this work, we propose a new method for retrieving similar MRI brain tumour images based on low level features like shape, texture, colour and fractal features. The benchmark BRATS dataset is used experiment. A total of 58 MRI images are used for experiment, out of which 16 are normal and 42 are abnormal MRI brain tumour images. The tumour is segmented using multi-level average thresholding and found to be effective in segmenting the tumours. And the CBIR system is implemented with high level semantics like tumour size, type of tumour etc. The proposed feature set is very effective in discriminating the tumours from normal MRI images.

Keywords: Content Based Medical Image Retrieval(CBMIR), low level features, MRI, Brain Tumour, Shape features, Texture features, Average Thresholding, Tagging

Introduction

A brain tumour (also called as intracranial neoplasm) usually occurs when there is a formation of abnormal cells in the brain. The brain tumours can be classified as two types, benign tumour and malignant or cancerous tumours. [1]. All types of brain tumours may produce symptoms like headaches, seizures, problem with vision, vomiting, and mental changes. The headache is classically worst in the morning and goes away with vomiting. More specific problems may include difficulty in walking, speaking and with sensation [2]. As the disease progresses unconsciousness may occur. The cause of most cases is unknown [1]. Risk factors that may occasionally be involved include a number of inherited conditions such as neurofibromatosis as well as exposure to the industrial chemical vinyl chloride, the Epstein-Barr virus, and ionizing radiation. While concern has been raised about mobile phone use the evidence is not clear. The most common types of primary tumours in adults are: meningiomas (usually benign), and astrocytomas such as glioblastomas [3]. The Figure 1.1 indicates the brain image with normal tissue and figure1.2 indicates the brain image with abnormal tissue

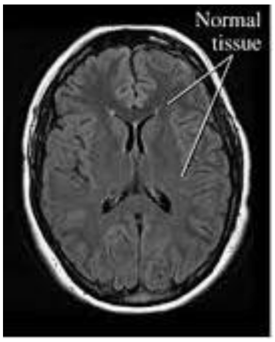

Figure 1.1: Normal tissue

Figure 1.2: Abnormal tissue

Based on the findings the tumours are divided into different grades of severity. Outcome varies considerably depending on the type of tumour and how far it has spread at diagnosis. Glioblastomas usually have poor outcomes while meningiomas usually have good outcomes.[3] The average five-year survival rate for brain cancer in the United States is 33%. Secondary or metastatic brain tumours are more common than primary brain tumours, with about half of metastases coming from lung cancer [1]. Primary brain tumours occur in around 250,000 people a year globally, making up less than 2% of cancers[1]. In children younger than 15, brain tumours are second only to acute lymphoblastic leukemia as a cause of cancer [3]. In Australia the average economic cost of a case of brain cancer is $1.9 million, the greatest of any type of cancer [4]. Content Based Image Retrieval (CBIR) systems can be used to retrieve images from a database which are similar to the query image [5]. CBIR is the application of computer vision. That has been one on the most vivid research areas in the field of computer vision over the decade. Instead of text based searching, CBIR efficiently retrieves images that are visually similar to query image. In CBIR query is given in the form of image. This paper aims to provide an efficient medical Image data Retrieval in Diagnosis Brain tumours.

Literature Review

Content-based retrieval for medical images is still in its infancy. Existing work in content based image retrieval mostly use CT scan image, mammogram x-ray images. Most CBIR systems concentrate mainly on two features namely the colour and texture. Wavelet descriptors have been used in many proposals including that achieves localization of shape features in both spatial and frequency domains. But wavelet descriptors have its disadvantages in that it requires intensive computation and are not rotation invariant. Some of the papers use colour histogram, colour moment and some use colour coherence vector. Only few literature works had concentrated on shape based features.

Lei et al presented colour features like colour histogram, colour moments, colour edge, colour correlograms. And texture features used are scenic depth, spatial distribution of tonal variation Surface orientation [6]. Here no shape feature is given much importance. In this paper Harlick features are given quiet a more importance. The Harlick features used in this paper are variance, contrast, correlation, Angular second moment, sum variance, sum entropy, entropy, Different variance, and difference entropy. Therefore in this paper around 8 texture features are being used. Empirical usability testing permits naïve users to provide information about the usability of individual system functions and components.

Y. Fanid Fathabad et al used colour features like Colour histogram, Colour moments. Texture features used are Energy, entropy. And Edge, corner, curvature, scale space and chain codes are the shape features used [7]. A good shape representation feature should be invariant to translation, rotation and scaling.

Amit kumar et al focused on the following color features they are Colour histogram, Colour moment, Colour coherence vector, Colour correlograms [8]. The texture feature used is Energy, entropy, Contract, correlation. The shape features used are Polygonal approximation, Moment invariant..

In Akila et al, various colour features like Colour histogram, Colour moment, Colour coherence vector and texture features like Energy, entropy, Contract and shape features like Edge, corner, curvature are extracted. The feature extraction of MRI images is accomplished here with the consideration of third order moment invariant functions [9].

Jaskirat Kaur et al, presented thresholding and edge detection being one of the important aspects of image segmentation comes prior to feature extraction and image recognition system for analyzing images. [10].

Proposed CBMIR Method

In the proposed Content Based Medical Image Retrieval (CBMIR) for brain tumours, the features are extracted for the images present in dataset and stored as feature database. For the query tumour image, the features are extracted and compared with existing tumours feature set. Based on similarity, various similar brain tumours are retrieved and displayed to the user as shown in figure 2.

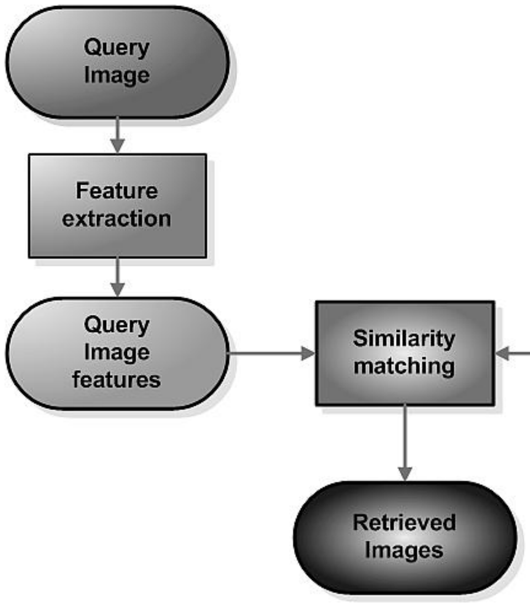

Figure 2: Proposed CBMIR method for MRI Brain tumours

Major Challenges

Some of the major challenges in the area of medical image retrieval are outlined as follows:

1. Extraction of robust and precise visual features from medical images is a difficult problem.
2. To be used as a diagnostic tool, the CBMIR systems need to prove their performance to be accepted by the clinicians.
3. Useful semantics for medical image retrieval needs to be established.

Dataset

BRAT's dataset with total 58 MRI brain tumour and normal images are used for experiment as shown in table 1.

Table 1: Dataset used for experiment

S. No	Type of Image	Number of images
1.	Normal MRI images	16
2.	Abnormal MRI tumour images	42

Multi-level Average Thresholding

Thresholding is used in our content based image retrieval to focus on ROI or to eliminate unwanted regions in the brain MRI image. The key parameter in the Thresholding process is the choice of the threshold value. Several different methods for choosing a threshold exist users can manually choose a threshold value. A simple method would be to choose the mean or median value, the rationale being that if the object pixels are brighter than the background, they should also be brighter than the average [11]. In a noiseless image with uniform background and object values, the mean or median will work well as the threshold, however, this will generally not be the case. When a normal Thresholding is applied over a brain MRI image the result would not be efficient hence a modified version of the conventional algorithm is performed where the background pixels are not considered while computing threshold value and the object pixels are alone considered for Thresholding as shown in Eqn 3.1

$$\text{Grey}_T = \sum_{i=0}^{n} \left(\frac{P_i}{n}\right) \qquad \text{------ 3.1}$$

Where P_i are the non-background pixels. n is total number of non-bckground pixels in the image.

The procedure for the performed Thresholding is given below.

Procedure:

1. Let B.P be background pixel's values (Black or RGB=0) and Let O.P object pixel's value
2. Let P be any pixel in an image and N be the total number of pixels in the image
3. If P <> B.P //not equal to background pixel
4. S = S+P;
5. Repeat from steps 3 to 4 for all pixels in the image
6. T=S/N; //T is average threshold value
7. Repeat step 8 for all pixels in the image
8. If P < T then set P == B.P
9. Save modified image.

The segmented brain tumour Region of Interest (ROI) as a result of Multi-Level Average Thresholding is shown in Figure 3.

Figure 3: Segmented of ROI by Multi-level Average Thresholding

Feature Extraction

In general, the shape of masses present in tumor is visually distinguishable and the same can be used for analysis and interpretation. The shape-based features can be categorized based on both the shape and margin of the mass. It has been observed that shape of a mass is considered to be relatively non-specific. This is due to the fact tumor categories of masses arise from one spot and grow circumferentially. The tumor masses are circular in shape and may also be of irregular shapes. As discussed earlier, shape of the ROI can be extracted for classifying the tumours. From shape of the ROI, we extract shape descriptors such as circularity, convex area, thinness ratio, equivalent diameter, eccentricity, compactness, entropy, shape index, standard deviation of edge, etc are extracted for the classification [11,12,13]. The various shape, texture, color and fractal features are used in this experiment as shown in Figure 4.

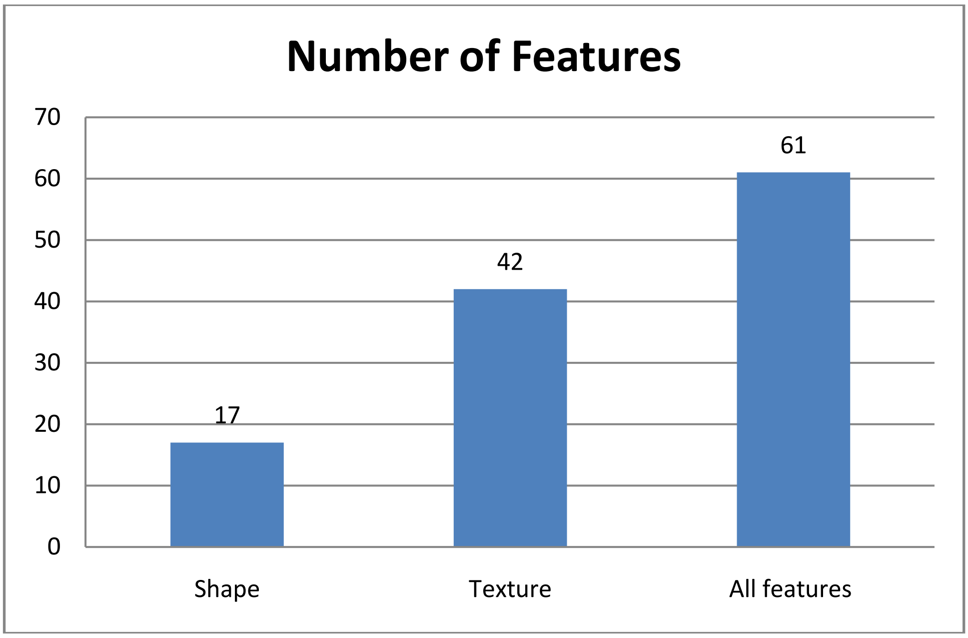

Figure 4: Brain Tumour feature set

In this work, 17 shape features are extracted from ROI. And these rotational and positional invariant geometric shape features are found to be effective in discriminating tumour masses For each ROI, the shape , texture, colour and fractal features are extracted and constructed as feature vector and is given below:

FV(img) = FV(shape) + FV(texture) + FV(color) +FV(fractal) ----------- *3.2*

Where $FV_{(S,M)}$ dimension is **total number**, *FV*(shape) and *FV*(texture) are features extracted from tumour ROI. BRATS 2012 dataset with a total of 58 brain MRI images are considered for experiment, where, 43 are tumor images and 13 are normal images. Various extracted shape properties for MRI brain tumour and normal images used in this experiment are shown in **Table 2**.

Table 2: Texture feature extracted from tumor and normal images

Image	Contrast	Contrast	Correlation	Correlation	Correlation	Correlation
ABNORMAL						
Abimg1	5.46	1.94	8.74	9.56	8.74	9.56
Abimg2	5.38	1.52	7.49	9.33	7.49	9.33
Abimg3	6.34	2.58	7.40	9.00	7.40	9.00
Abimg4	7.12	4.30	8.57	9.16	8.57	9.16
NORMAL						
Nimg1	1.66	1.77	5.68	5.39	5.68	5.39
Nimg2	6.58	6.88	7.97	7.88	7.97	7.88

From above table it is evident that, the features contrast (contrast), correlation (correlation), effectively discriminate the normal and abnormal brain tumour images. The value of contrast ranges from 5.38 to 7.12 for abnormal images and ranges from 1.66 to 6.58 for normal images.

Table 3: Shape feature measures of tumor and normal images

Image	Cltr Prom	Cltrprom	CltrShade	CltrShade	Dissimilar	Dissimilar
ABNORMAL						
Abimg1	1.21	1.35	9.51	1.05	8.97	3.43
Abimg2	4.86	6.51	4.07	5.18	9.09	3.00
Abimg3	5.90	7.48	4.79	5.86	1.09	4.91
Abimg4	1.38	1.49	1.08	1.16	1.16	6.99
NORMAL						
Nimg1	3.40	3.33	3.85	3.80	2.25	2.32
Nimg2	8.48	8.50	7.23	7.24	1.64	1.84

From above table it is evident that, the features cluster prom(cltrProm), cluster shade(cltrShade),Dissimilarity (Dissimilar) effectively discriminate the normal and abnormal brain tumour images. The value of Dissimilarity ranges from 3.00 to 6.99 for abnormal images and ranges from 1.84 to 2.32 for normal images.

Table 4: Harlick feature measures of tumor and normal images

Sumenty	Sumenty	Diffvar	Diffvar	Diffentr	Diffentr	IMC	IMC	IMC2	IMC2
ABNORMAL									
0.30	0.27	0.54	0.19	0.12	0.06	-0.64	-0.82	0.51	0.57
0.23	0.21	0.53	0.15	0.13	0.05	-0.54	-0.78	0.42	0.49
0.32	0.31	0.71	0.43	0.14	0.09	-0.61	-0.74	0.51	0.56
0.31	0.29	0.59	0.26	0.13	0.08	-0.60	-0.77	0.50	0.55

NORMAL									
0.91	0.93	1.65	1.76	0.68	0.70	-0.22	-0.19	0.49	0.45
0.72	0.72	0.65	0.68	0.38	0.39	-0.46	-0.45	0.62	0.61

From above table it is evident that, the features sum entropy (sumenty), Difference variance (Diffvar), effectively discriminate the normal and abnormal brain tumour images. The value of Diffentr ranges from 0.05 to 0.09 for abnormal images and ranges from 0.39 to 0.70 for normal images.

Experimental Results

The interface developed has features like upload that is used to upload the query image, compare all that is used compare different images stored in the database. Along with this there is one more feature i.e., the update feature update next image for further comparisons. The Figure 5 and Figure 6 are results of the interface to compare abnormal images

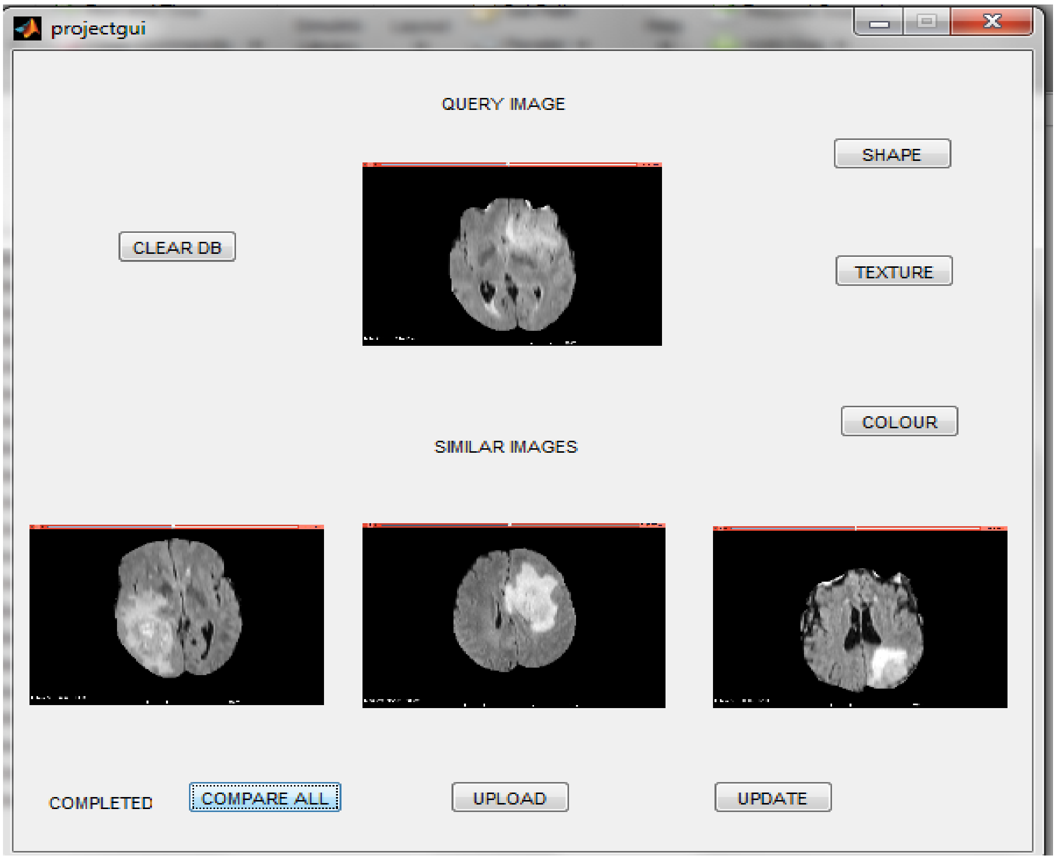

Figure 5: Interface to compare tumor images

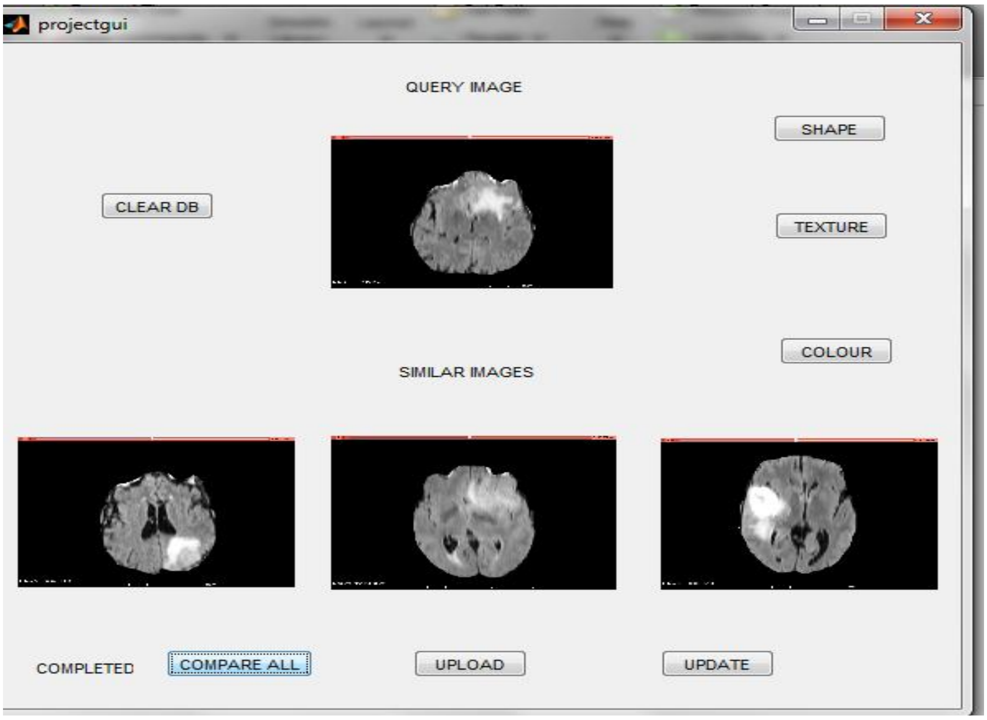

Figure 6: Interface to compare tumor images

The Figure 7 and 8 are the results of the interface to compare normal images

Figure 7: Interface to compare normal images

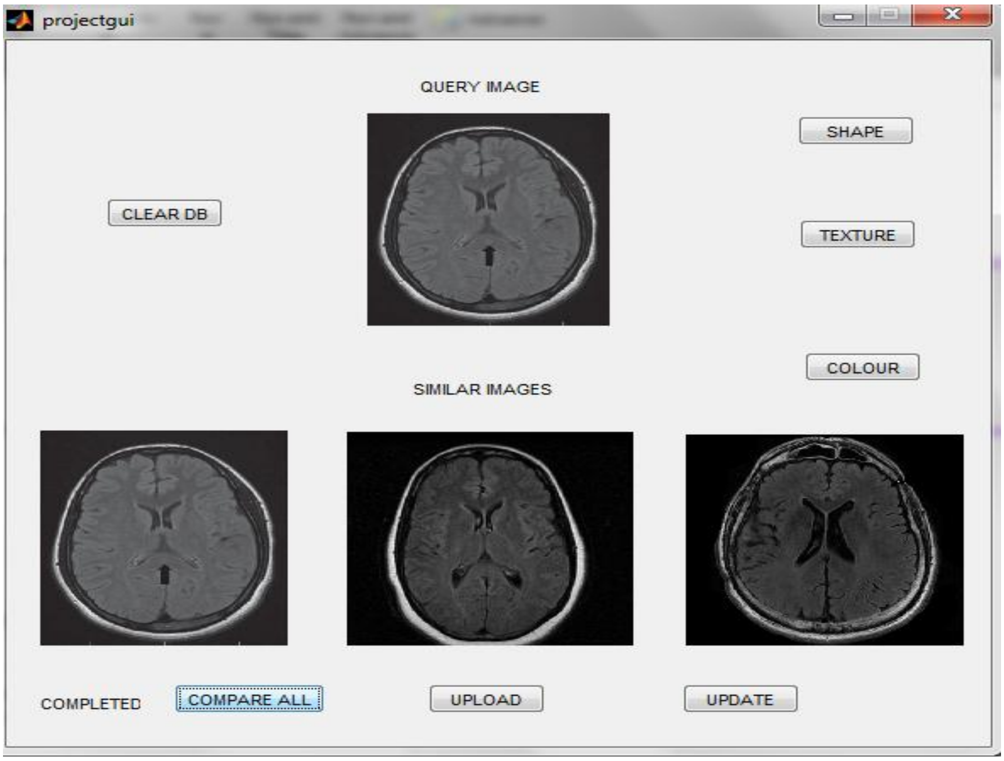

Figure 8: Interface to compare normal images

The Figure 9 are the results of the interface for tagging (semantics)

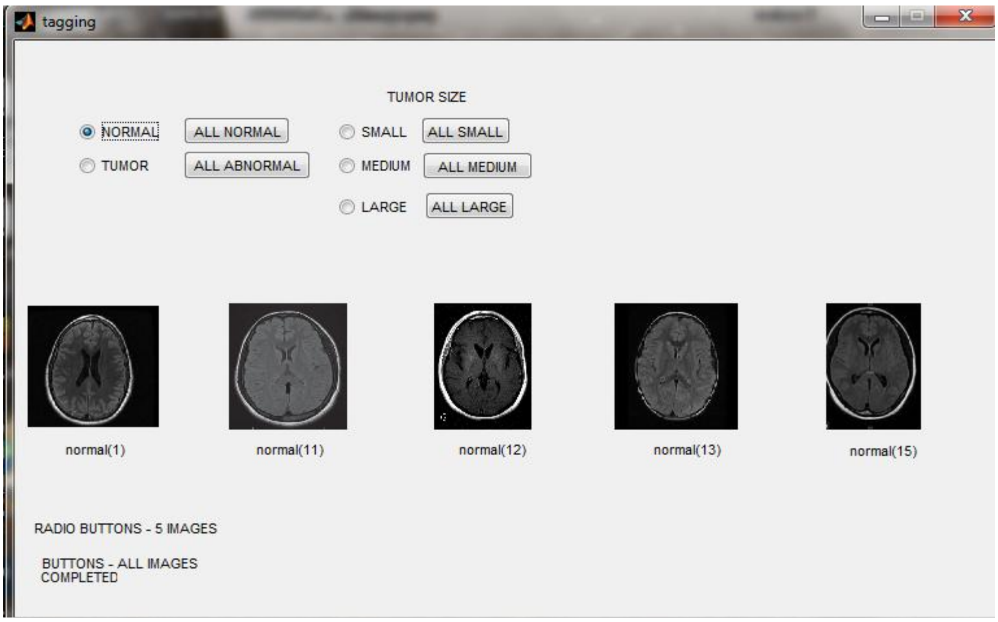

Figure 9: Interface for tagging (Semantics)

The best features obtained using cfs subset evaluation method are as follows:

1. Centroid
2. min-axis
3. Solidity
4. Extent
5. Boundbox1
6. Correlation1
7. Dissimilarity1
8. Energy
9. Entropy
10. Homogenity3
11. Sum entropy
12. Difference entropy1
13. Correlation.

The cases to variable ratio is one of the measure to test the effectiveness of the features extracted [12,13]. The cases to variable ratio for shape, texture and all features for 58 MRI image are shown in table below,

Table 5: C/v ratio for feature set

Feature	Number of Features	C/v ratio
Shape	17	3.41
Texture	42	1.38
All features (shape, texture, color & fractal)	61	0.95

The c/v ratio for various set of features used in this work are shown in Figure 10 below

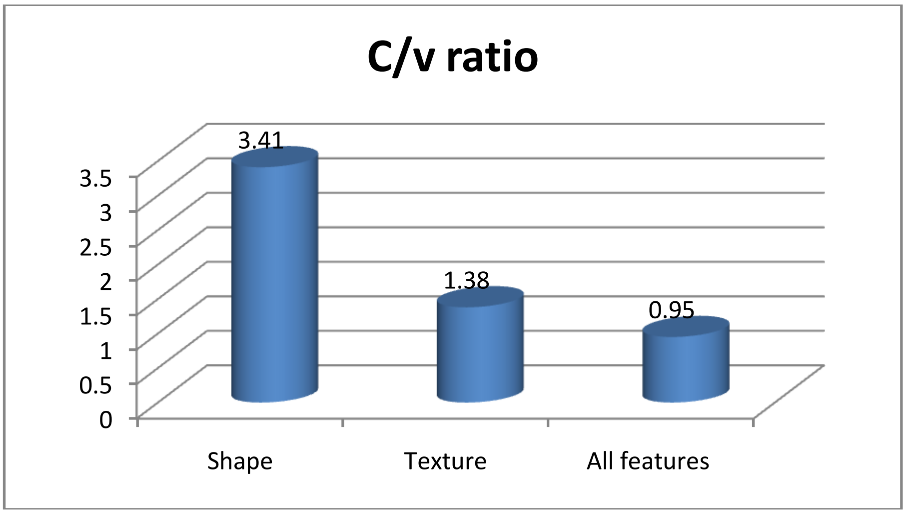

Figure 10: c/v ratio for various feature set

Conclusion

A content based medical image retrieval system was developed for BRATS brain MRI tumour images by extracting various shape, GLCM, colour and fractal features. The Region of Interest (ROI) of brain tumour is extracted using Multi-Level Average Grey Thresholding approach. The proposed CBMIR system is found to be effective and provide as clinical aid or training tool for radiologists. The extracted shape and other features are found to be effective in discriminating the various brain tumours from normal images. The c/v ratio for various features are extracted and found to be effective. As a feature work, various vital features are need to be extracted from tumour ROI using feature selection methods, in order to increase the c/v ratio.

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