Detection of brain tumors in brain images based on Pseudo Coloring and spatial methods

Article *in* ARPN Journal of Engineering and Applied Sciences · January 2018

DOI: 10.3923/jeasci.2018.6123.6129

2 authors, including:

Faisel Ghazi Mohammed
University of Baghdad

Journal of Engineering and Applied Sciences 13 (15): 6123-6129, 2018
ISSN: 1816-949X

Detection of Brain Tumors in Brain Images Based on Pseudo Coloring and Spatial Methods

[1]Mina H. Madhi and [2]Faisel G. Mohammed
[1]Al-Mansour University College, Baghdad, Iraq
[2]Department of Remote Sensing and GIS, College of Science,
University of Baghdad, Baghdad, Iraq

Abstract: The brain is a greatly particular organ and works as the controller for body functions of all actions, feelings and emotional states. It is well-known that each portion of the brain has a particular of an overpoweringly imperative function and each portion adds healthful performance of human body. The tumors position in the brain is critical determinant that affect on brain tumor on person's activity and caused indications. Tumors can be arisen in brain by reason of the unrestrained expansion of cells. They can be remedied if it is well-timed identified by suitable treatment. This study proposes programmed recognition and diagnosis of brain tumors based on image binarization, segmentation based on YCbCr, smoothing, histogram equalization, density slicingand object labeling. Based on various collected tumor images from Iraqi hospital, the proposed method of this study has detection rate of better than 99 with speedy processing.

Key words: Tumor brain detection, image binarization, segmentation based on YCbCr, smoothing, histogram equalization, density slicing and object labeling

INTRODUCTION

Brain tumors initiate from irregular cells expansion that thrive in an abandoned approach. They arrive from brain cells across the brain membranes (meninges) and nerves or glands. They can be explicitly smashup brain cells or impairment cells through on condition that additional pressure passing through the skull (Haj-Hosseini *et al*., 2016). Brain tumors are shown in Fig. 1. Malignant tumors are the most risky tumor instigating 14000 deaths annually. In spite of extensive academic attempts in research for frequent decades, the average Overall Survival (OS) is still at merely 15 months for the malignant glioma, Glioblastoma Multiform (GBM) (Liu *et al*., 2016). In accordance with tumor harshness rank, it can be classified into diverse grades. In first grade, minimum dangerous tumor are typically interrelated with protracted endurance. They develop steadily and essentially possess a typical form through a microscope and surgery cure may be efficacious for this tumor variety as in gangliocytoma, ganglioglioma and pilocytic astrocytoma. The objective of MRI segmentation is to fragment a picture into standardized regions and henceforward discovering the region outlines (Janani and Meena, 2013; Dong *et al*., 2010). MRI scan does not use radiation and it is more operative than CT scan (Patel and Doshi, 2014). Tumor involves numerous organic tissues just particular type of MRI has not possibility to provide complete details about abnormal tissues. Linking distinguishing corresponding information can promote the segmented region. Characteristics of MR images used for segmentation have weighted three pictures (T2, T1 and Proton Density (PD)) per slice axial. The segmentation approaches were completely in effect particularly in the development phases of diseased tissues (Kabade and Gaikwad, 2013; Aslam *et al*., 2013; Sehgal *et al*., 2006).

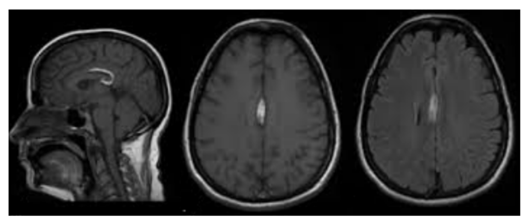


Fig. 1: Tumor brain varieties

Literature review: Imaging is an important feature of medical science to envisage the bodily structures of the humanoid body (Chen *et al*., 1998; Connolly and Fleiss, 1997). Numerous newfangled multifaceted multidimensional digital images of biological structures can be handled and employed to imagine concealed

Corresponding Author: Mina H. Madhi, Al-Mansour University College, Baghdad, Iraq

analytical features that are either problematic or unmanageable to recognize using planar imaging approaches. Segmentation is an essential method in most medicinal image investigation and cataloguing for radiological assessment by computerized diagnosis simulators (Dhawan, 1990). Principally, image segmentation approaches are possibly to be categorized into edge based, region-based (Tsai and Chang, 2003) and pixel-based approaches. k-means clustering is a key technique in pixel based methods. For the reason that pixel-based approaches using k-means clustering are uncomplicated and the computational complication is comparatively lower and practicable than other region-based or edge-based methods. Additionally, it is appropriate for medical image segmentation as the number of clusters is typically recognized for images of specific districts of the hominid anatomy (Chen *et al*., 1998; Connolly and Fleiss, 1997; Dhawan, 1990; Gonzalez and Woods, 2002; Ng *et al*., 2006). The enhancements realized by Chen *et al*. (1998), Connolly and Fleiss (1997), Dhawan (1990), Gonzalez and Woods (2002) and Ng *et al*. (2006) were noteworthy, nonetheless additional computational complication and additional software functionality are necessitated.

Various algorithms and segmentation methods have been reported to discover irregularities in the brain by means of MRI image like Brain tumor. By Kowar and Yadav (2012), a new method for the detection of tumor in brain using segmentation, histogram and thresholding has been presented. By Rajesh and Bhalchandra (2012), Meyer's flooding watershed procedure for segmentation as well as the morphological set-up have achieved using MATLAB simulator.

In this study, programmed technique has been suggested to identify brain tumor at image and lesion levels. The projected approach consists of several steps image binarization, segmentation based on YCbCr, smoothing, histogram equalization, density slicingand object labeling. This method has the properties of simplicity, prompt detection with high level of tumor detection.

MATERIALS AND METHODS

A computerized structure is presented for brain tumor detection at the image based on pseudo coloring and spatial methods. The proposed system can be verified on MRI. Tumor recognition in MRI is more effectual owing to its high contrast, low radiation and spatial resolution. MR images provide info about a brain tumor size and its location but they cannot classify the tumor grade. Doctors for that reason, continuing to an insidious system of spinal tap and biopsy take long time and hurting. This incapability boosts more exact system to improve the recognition ability of MR images. Additionally, the preliminary stage doesn't necessitate going for a surgery as the intention of proposed system is to categorize the brain tumors by means of MR images. The proposed method involve many steps such as image binarization, segmentation based on YCbCr, smoothing, histogram equalization, density slicingand object labeling as shown in Fig. 2. This proposed automatic system aids in highest detection and effectual supply of swift outcomes in medical consequences.

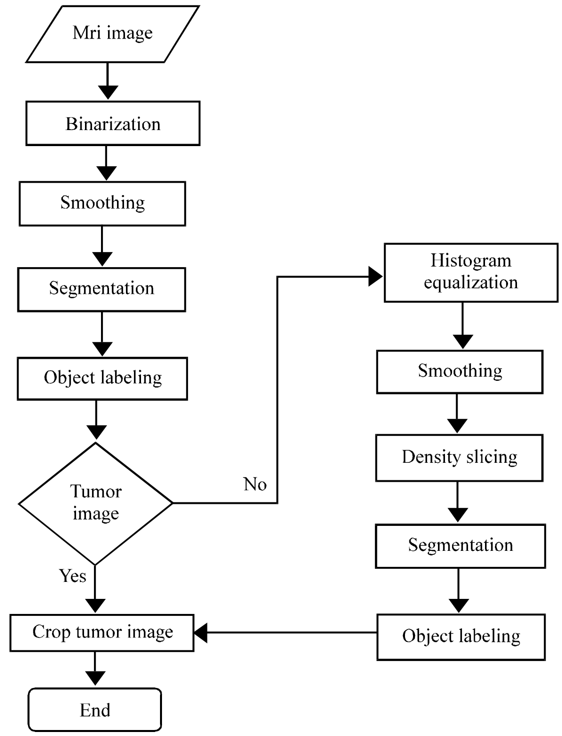


Fig. 2: Proposed methodology

Image preprocessing: For the best result of the image segmentation process, the image must be preprocessed. In our method, pre-processing involves two steps. The first step is to remove the extra parts of the image such as the writings of the MRI devices and to keep the images of the brain only this is done by the cropping. The second step is to resize the image, reduce it to a quarter to improve the processing speed and get the results in a short time.

Image binarization: The binarization technique converts the photo (0-256 gray ranges) in to black and white photo (0 or 1). The excessive first-rate binarized photo can provide extra accuracy in segmentation and different picture processing steps as match with authentic photo due to the fact noise is gift within the authentic photo. The algorithms divide into two classes global binarization local binarization. The global binarization techniques used single threshold for entire photo and the local binarization technique in which the threshold calculated regionally pixel via pixel or area via. area. In proposed method the global binarization method (fixed thresholding) used. In fixed thresholding binarization method (Liu *et al*., 2016; Janani and Meena, 2013; Dong *et al*., 2010) fixed threshold value is used to assign 0's and 1's for all pixel positions in a given image. In this fixed threshold method the threshold is selected depending on the principle of try and error and in our proposed method the value of threshold was 130 to give the best results. The formula of binaraization as follows:

$$g(x, y) = \left\{ {}^{1}_{0} \text{ if } f(x, y)>th \right.$$

Where:

th = The threshold and equal 130
f(y, x) = Original image
g(x, y) = Binarized image

Histogram equalization: Histogram equalize attempt to re-distribute values across the brightness spectrum with roughly the same amount of pixels at each brightness level. Histogram equalize algorithm steps:

First, tally the amount of each color (i.e., build the histogram):

Histogram (Pixel-Value) = Histogram (Pixel-Value)+1

Compute scaling factor:

$$\text{Scale factor} = \frac{255}{(\text{i Width}\times\text{i Height})}$$

Handle pixel values as following (CDF):

Histogramm (0) = Histogramm (0)×scale factor x : 1.255 Do:

New histogram (x) = Histogram (x-1)+
(scale factor×Histogramm (x))

Integrate all the look-up values and draw new histogram:

x: 1, 255 Do:
New histogram (x) = Integer (new hhistogram (x))

If:
New histogram (x)>255 then new histogram (x) = 255

Apply the equalized values and draw picture: For all picture pixels in the range x, y do:

New pixel (x, y) = New histogram (old pixel (x, y)))

Image smoothing: Smoothing is one of the denoising methods. Smoothing basically acts as low pass filtering and high frequency components such as edges and boundaries are removed, rather replaced by either average or mean values of gray scale values of all the pixels. Suppose due to poor lighting the image quality is not proper which could be enhanced by using any smoothing domain filters whereas denoising includes all image enhancement methods in spatial as well as transform domain. Smoothing is basically a blurring process. It is frequently used in image processing (Gonzalez and Woods, 2002). In this study, image smoothing was used not to noise remove but also used as skull remover. Specific mask value was used to achieve remove all noise and skull.

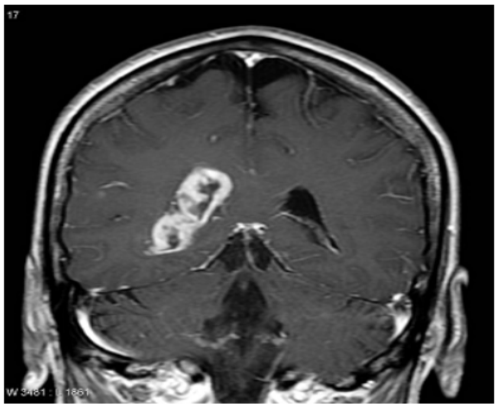
Density slicing: Intended for detection of brain tumors, information's are taken from local and publicly datasets that have anomalous MR images. The objects in MR images are to be abolished and so, preprocessing can be realistic (Kowar and Yadav, 2012). Density slicing is one of methods that used in digital data interpretation and analysis. A technique normally applied to a single-band monochrome image for highlighting areas that appear to be uniform in tone but are not. Image pixel values 0-255 are converted into a series of intervals (into different ranges) or slices and different colors are assigned to each slice (range) in the output image. Density slicing is sometimes referred to as "double threshold". Figure 3 shows the output of density slicing step. In the present research, the image was divided into five parts to control the tumor gray tone and then perform the segmentation process correctly. The algorithm for density slicing is as follows:

Algorithm 1; Dencity slicing:

1. Define array that contain colors value for each pixel and all colors band (R, G and B)
2. Define the loops to scan all image pixels (i for image rows and j for image columns)
3. Determine the rang of each slice and set RGB values as follows:

```
For i = 0-55
   Array (i).R = 0         Array (i).G = 0          Array (i).B = 255
  End for
  For i = 0-55: j = i+55
   Array (j).R = 0        Array (j).G = 255       Array (j).B = 0
  End for
  For i = 0-55: j = i+110
   Array (j).R = 255      Array (j).G = 255      Array (j).B = 0
  End for
  For i = 0-55: j = i+165
   Array (j).R = 255      Array (j).G = 100      Array (j).B = 0
  End For
  For i = 0-35: j = i+220
   Array (j).R = 255      Array (j).G = 255      Array (j).B = 255
  End for
```

(a)



(b)

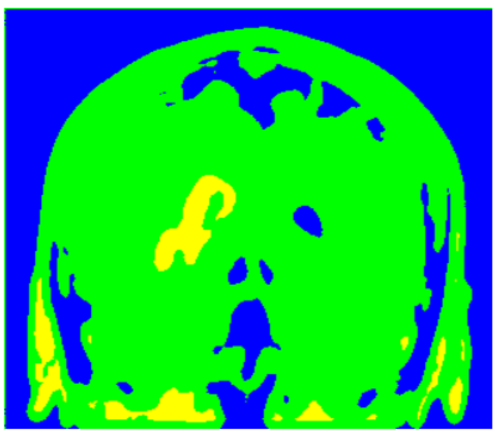


Fig. 3a, b: Density slicing step

Segmentation based YCbCr color transformation: We use image segmentation in the brain magnetic resonance images to reach the tumor directly. In this study, image segmentation depends on YCbCr color transformation. YCbCr is a color space can be adopted as measure of the color image pipeline in photography systems. YCbCr is not a complete color space but it stands for a procedure of encoding RGB data. The displayed authentic color is based on the used authentic RGB primaries to show the signal. It has one luminance constituent (Y) and dual chrominance constituents (Cb and Cr) where Cb is the chrominance-blue constituent and Cr is the chrominance red constituent. The YCbCr image is feasibly transformed to/from RGB image (Powar *et al*., 2011). The color transformation was used to reduce decorrelation between image pixels and fixing the color value. The transformation matrix to convert from RGB to YcbCr color space shown:

$$\begin{pmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{pmatrix}$$

This matrix was used to find values of Y, Cb and Cr as shown:

$$\begin{matrix} Y \\ Cb \\ Cr \end{matrix} = \begin{matrix} R \\ G \\ B \end{matrix} \begin{pmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{pmatrix}$$

And final result of segmentation comes from compare the value of y chromosome the specific threshold (Selected experimentally) as follows:

$$\text{Output} = \begin{cases} 0 \text{ if } \ y>\text{ThrY}+10 \ \ 0\text{ry}<\text{ThrY}-10 \ \ 0\text{ry} = \text{ThrY} \\ 255 \text{ otherwise} \end{cases}$$

where (ThrY) selected experimentally and equal 128.

Object labeling: The proposed technique labels every element by using rapid and occasional complexity contour tracing approach. This approach is based totally at the precept which element is completely decided via. its contours. This approach additionally affords a technique for locating all element pixels. An photo will scan within the identical manner as it'd be encountered via. a scanner, i.e., from the top to the backside and from left to right in keeping with every line. Whilst an external or inner contour is encountered then the contour-tracing technique will use to finish the contour and assign a label, say L to all pixels at the contour. Whilst the contour is traced returned to its place to begin, scanning will resume at that factor. Afterward while the contour pixels labeled L are visited once more then the identical label L will assign to black pixels that lie subsequent to them. This technique is relevant in areas wherein ought to stumble on elements and additionally classify them through contour capabilities. The following pseudo codes display in details the implementation of proposed set of rules. The crucial exquisite had confirmed earlier than every ambiguous step:

Algorithm 2; Set label (detected object) as matrix have dimensions TMP:

```
Width and tmpheight
   Set rep as no of iteration-1
   Amount: = 1000
   Begin
   For j: = 0 to rep
   n: = 1
   fwdscan: (Forwarded scan)
   for x: = 1 to tmpheight-2 do begin
   for y: = 1 to tmheight-2 to begin
     mask [0]: = label [x-1, y-1]
     mask [1]: = label [x, y-1]
     mask [2]: = label [x+1, y-1]
     mask [3]: = label [x-1, y]
     mask [4]: = label [x, y]
    if img BW [x, y]: = 1 then
```

```
   temp: = mask [0] or mask [1] or mask [2] or mask [3]
   if temp: = 0 then begin
       label (x, y): = n; bscan = 1; n: = +1
Else
   min: = mask [0]
   for i: = 1 to 4 do begin
       if min: = 0 then min = mask [i]: cont
   if mask [i]<min and mask [i] <>0 then
   min = mask (i); cont;
  End
  label 1[x, y]: = min; bscan: = 1
  End
  End
```

Algorithm 3; Backscan:

```
for x: = 1 to tmpwidth-2 do begin
for y: = 1 to tmpwidth-2 do begin
if label ((tmpwidth-1)-x, (tmpheight-1)-y)
<> 0 then begin
mask [0] = label [[tmpwidth-1]-[x-1]
[tempheight-1]-[y-1]]
mask [1] = label [[tmpwidth-1]-[x
[tmpheight-1]-[y-1]]
mask [2] = label [[tmpwidth-1]-[x+1]
[tmphight-1]-[y-1]]
mask [3] = label [[tmpwidth-1]-[x-1]
[tmpheight-1]-y]
mask [4] = label [[tmpwidth-1]-x, [tmpheight-1]-y
min = mask [0]
for i: = 1 to 4 do begin
If min = 0 then min = mask (i): Go to cont 2
IIF mask (i)<min and mask (i) <> 0 then min = mask [i]
cont 2:
End
for y: = 0 to tmheight-1 do begin
   for x: = 0 to tmheight-1 do begin
   count [label [x, y], 0]: = count [label (x, y), 0)+1
Set all the min and max coordinate of x and y to min 1st, ...
   if count [label [x, y], 1]: = 0 then do begin
        count [label 1 [x, y], 1]: = x
        count [label 1 [x, y], 2]: = x
        count (label 1 (x, y), 3): = y
        count (label 1 (x, y), 4): = y
   End
Update each coordinate
update each coordinate
update coordinate x min (if x<than the previous values)
   if x<count [label 1 [x, y], 1] and count [label [x, y], 1)<>
   0 then count [label 1 [x, y], 1] = x
   if x>count [label 1 [x, y], 2] and count [label 1[x, y], 2 <>
   0 then count [label 1 [x, y], 3 and count [label 1 [x, y],
          3]<>0 then count [label 1 [x, y], 3] = y
   if y>count [label 1 [x, y], 4] and count[label[x, y], 4]
        <> 0 then count[label[x, y], 4] = y
    End
End
```

RESULTS AND DISCUSSION

All procedural steps have been run in visual basic simulator using 2.67 GHz i5 CPU and 3 Gbyte RAM of the computer device. This model can do the tumor detection algorithm by their corresponding buttons of image binarization, segmentation based on YCbCr, smoothing, histogram equalization, density slicing and object labeling. The investigational results of MR brain tumor images are depicted Fig. 4-6. It must be indicated that the average success rate for proposed model is better than () for local image sets collected from Iraqi hospitals. This model can be used to detect tumor brain image from any image from any hard disk (internal or external) or from any external storage memory or any related dataset.

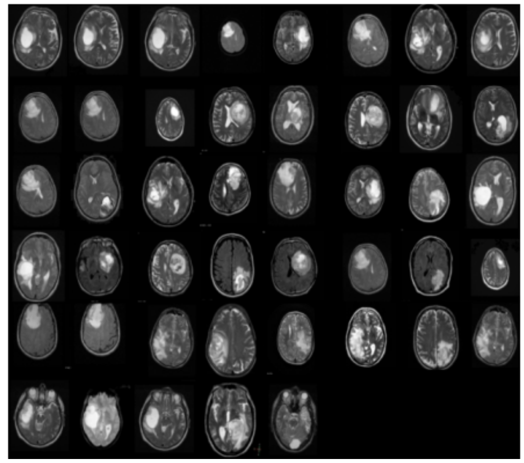


Fig. 4: Orignal dataset

Fig. 5: Segmented dataset

If the tumor is not correctly allocate using the first method then go to the second method as shown in Fig. 7 because it has a detectable tumor in the most complex images. In addition to simplicity and GUI facilities by visual basic 6 simulator, the proposed tumor detection in this study has better accuracy than (Sudharani *et al*., 2016; Nabizadeh *et al*., 2014; Abdel-Maksoud *et al*., 2015) as depicted by Table 1.

Table 1: Comparison of the suggested tumor detection in this study with Sudharani *et al.* (2016), Nabizadeh *et al.* (2014) and Abdel-Maksoud *et al.* (2015)

Method	Simulator	Average accuracy (%)
Sudharani *et al.* (2016)	MATLAB	89.20
Nabizadeh *et al.* (2014)	MATLAB	91.50
Abdel-Maksoud *et al.* (2015)	MATLAB	95.06
Proposed at present	Visual basic	99.00

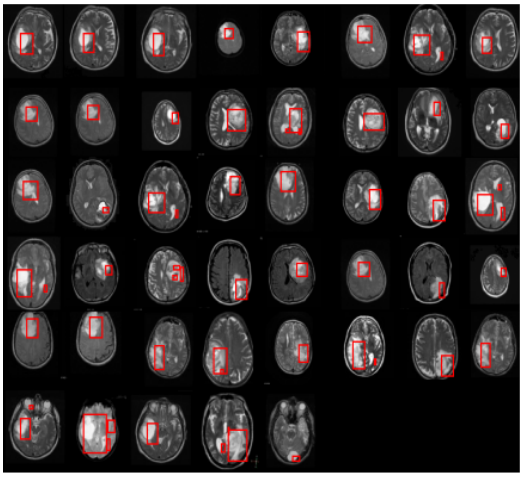


Fig. 6: Labelled dataset

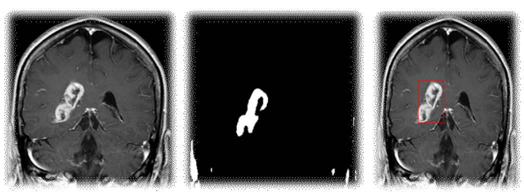


Fig. 7: Results of secound method

CONCLUSION

MRI images are highly apposite for brain tumor recognition. In this study, digital image processing approaches are imperative for brain tumor detection by MRI images. The preprocessing method involves density slicing process. The preprocessed images have been employed for post processing procedures of image binarization, segmentation based on YcbCr, smoothing, histogram equalization, density slicingand object labeling. It must be indicated that the success rate for proposed model is better than 99 in average. This model can be used to detect tumor brain image from any image from any internal or external related dataset from any storage memory with swift detection results.

Tumor brain image from any image from any internal or external related dataset from any storage memory with swift detection results.

REFERENCES

Abdel-Maksoud, E., M. Elmogy and R. Al-Awadi, 2015. Brain tumor segmentation based on a hybrid clustering technique. Egypt. Inf. J., 16: 71-81.

Aslam, H.A., T. Ramashri and M.I.A. Ahsan, 2013. A new approach to image segmentation for brain tumor detection using pillar K-means algorithm. Intl. J. Adv. Res. Comput. Commun. Eng., 2: 1429-1436.

Chen, C.W., J. Luo and K.J. Parker, 1998. Image segmentation via adaptive K-mean clustering and knowledge-based morphological operations with biomedical applications. IEEE. Trans. Image Process., 7: 1673-1683.

Connolly, C. and T. Fleiss, 1997. A study of efficiency and accuracy in the transformation from RGB to CIELAB color space. IEEE. Trans. Image Process., 6: 1046-1048.

Dhawan, A.P., 1990. A review on biomedical image processing and future trends. Comput. Methods Programs Biomed., 31: 141-183.

Dong, B., A. Chien and Z. Shen, 2010. Frame based segmentation for medical images. Commun. Math. Sci., 32: 1724-1739.

Gonzalez, R.C. and R.E. Woods, 2002. Digital Image Processing. 2nd Edn., Prentice Hall, Upper Saddle River, New Jersey, USA., ISBN:9780130946508, Pages: 793.

Haj-Hosseini, N., P. Milos, C. Hildesjo, M. Hallbeck and J. Richter *et al*., 2016. Fluorescence spectroscopy and optical coherence tomography for brain tumor detection. Proceedings of the International Conference on SPIE Photonics Europe, Biophotonics: Photonic Solutions for Better Health Care, April 3-7, 2016, SPIE-International Society for Optical Engineering, Brussels, Belgium, pp: 9887-9896.

Janani, V. and P. Meena, 2013. Image segmentation for tumor detection using fuzzy inference system. Intl. J. Comput. Sci. Mobile Comput., 2: 244-248.

Kabade, R.S. and M.S. Gaikwad, 2013. Segmentation of brain tumour and its area calculation in brain MR images using K-mean clustering and fuzzy C-mean algorithm. Int. J. Comput. Sci. Eng. Technol., 4: 524-531.

Kowar, M.K. and S. Yadav, 2012. Brain tumor detection and segmentation using histogram thresholding. Int. J. Engin. Advan. Technol., 1: 2249-8958..

Liu, Y., A. Carpenter, H. Yuan, Z. Zhou and M. Zalutsky *et al*., 2016. Gold nanostar as theranostic probe for brain tumor sensitive PET-optical imaging and image-guided specific photothermal therapy. Cancer Res., 76: 4213-4213.

Nabizadeh, N., N. John and C. Wright, 2014. Histogram-based gravitational optimization algorithm on single MR modality for automatic brain lesion detection and segmentation. Expert Syst. Appl., 41: 7820-7836.

Ng, H.P., S.H. Ong, K.W.C. Foong, P.S. Goh and W.L. Nowinski, 2006. Medical image segmentation using K-means clustering and improved watershed algorithm. Proceedings of the 2006 IEEE Southwest Symposium on Image Analysis and Interpretation, March 26-28, 2006, IEEE, Washington, DC, USA., pp: 61-65.

Patel, J. and K. Doshi, 2014. A study of segmentation methods for detection of tumor in brain MRI. Adv. Electron. Electr. Eng., 4: 279-284.

Powar, V., A. Jahagirdar and S. Sirsikar, 2011. Skin detection in YCbCr color space. Intl. J. Comput. Appl., 2011: 1-4.

Rajesh, C.P. and A.S. Bhalchandra, 2012. Brain tumour extraction from MRI images using MATLAB. Intl. J. Electron. Commun. Soft Comput. Sci. Eng., 2: 1-4.

Sehgal, V., Z. Delproposto, D. Haddar, E.M. Haacke and A.E. Sloan *et al*., 2006. Susceptibility-weighted imaging to visualize blood products and improve tumor contrast in the study of brain masses. J. Magn. Reson. Imaging, 24: 41-51.

Sudharani, K., T.C. Sarma and K.S. Prasad, 2016. Advanced morphological technique for automatic brain tumor detection and evaluation of statistical parameters. Procedia Technol., 24: 1374-1387.

Tsai, C.S. and C.C. Chang, 2003. An improvement to image segment based on human visual system for object-based coding. Fundam. Inf., 58: 167-178.