SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

November 2018

TUMOUR DETECTION USING SEGMENTATION

A Project Report

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ABSTRACT

Biomedical Image Processing is a growing and demanding field. It comprises of many different types of imaging methods likes CT scans, X-Ray and MRI. These techniques allow us to identify even the smallest abnormalities in the human body. The primary goal of medical imaging is to extract meaningful and accurate information from these images with the least error possible. To give better discovery of tumour without influencing an ordinary tissue is exceptionally difficult process. Out of the various types of medical imaging processes available, MRI is the most reliable and safe. It does not involve exposing the body to any sorts of harmful radiation. This MRI can then be processed, and the tumour can be segmented. Tumour Segmentation includes the use of several different techniques. The whole process of detecting tumour from an MRI can be classified into four different categories: Pre-Processing, Segmentation, Optimization and Feature Extraction. The performance of the computer aided detection system is approximately 84.26% of accuracy in detection of tumours.

BACKGROUND

Tumours affect the humans badly, because of the abnormal growth of cells within the affected organ. It can disrupt proper brain function and be life-threatening. Two types of brain tumours have been identified as benign tumours and malignant tumours. Benign tumours are less harmful than malignant tumours as malignant are fast developing and harmful while benign are slow growing and less harmful. Medical imaging technique is used to create visual representation of interior of the human body for medical purposes and noninvasive possibilities can be diagnosed by this technology. The various types of medical imaging technologies based on non-invasive approach like; MRI, CT scan, Ultrasound, SPECT, PET and X-ray. When compared to other medical imaging techniques, Magnetic Resonance Imaging (MRI) is majorly used and it provides greater contrast images of the brain and cancerous tissues. Therefore, tumour identification can be done through MRI images. This project focuses on the identification of tumour using image processing techniques.

OVERVIEW AND PLANNING REVIEW

Image Acquisition:

First step is to acquire the CT scan image of patient. The CT images are having low noise when compared to X-ray and MRI images; hence they are considered for developing the technique. The main advantage of using computed tomography images is that, it gives better clarity and less distortion. DICOM (Digital Imaging and Communications in Medicine) has become a standard for medical Imaging.

The acquired images are in raw form. In the acquired images lot of noise is observed. To improve the contrast, clarity, separate the background noise, it is required to pre-process the images. Hence, various techniques like smoothing, enhancement are applied to get image in required form.

Binarization:

Binarization approach depends on the fact that the number of black pixels is much greater than white pixels in normal images (with no tumours), so we started to count the black pixels for normal and abnormal images to get an average that can be used later as a threshold, if the number of the black pixels of a new image is greater that the threshold, then it indicates that the image is normal, otherwise, if the number of the black pixels is less than the threshold, it indicates that the image in abnormal.

Erosion and Dilation:

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze.

Segmentation divides the image into its constituent regions or objects. The result of image segmentation is a set of segments that collectively cover the entire image or a set of contours extracted from the image. Marker-controlled watershed segmentation follows this basic procedure.

1) Compute a segmentation function. This is an image whose dark regions are the objects you are trying to segment.
2) Compute foreground markers. These are connected blobs of pixels within each of the objects.
3) Compute background markers. These are pixels that are not part of any object.
4) Modify the segmentation function so that it only has minima at the foreground and background marker locations.
5) Compute the watershed transform of the modified segmentation function.

Feature Extraction:

This stage is an important stage that uses algorithms and techniques to detect and isolate various desired portions or shapes of a given image. When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant, then the input data will be transformed into a reduced representation set of features. The basic characters of feature are area, perimeter and eccentricity. These are measured in scalar. These features are defined as follows:

A) Area: It is the scalar value that gives actual number of overall nodule pixel in the extracted ROI. Transformation function creates an array of ROI that contains pixels with 255 values.

Area = A = (Ai,j , X ROI[Area] = I , Y ROI[Area] = j)

Where, i, j are the pixels within the shape. ROI is region of interest. X ROI[ ] is vector contain ROI x position, Y ROI[ ] is vector contain ROI y position.

B) Perimeter: It is a scalar value that gives actual number of the nodule pixel. It is the length of extracted ROI boundary. Transformation function create array of edge that contain pixel with 255 values that have at least one pixel which contain 0 values.

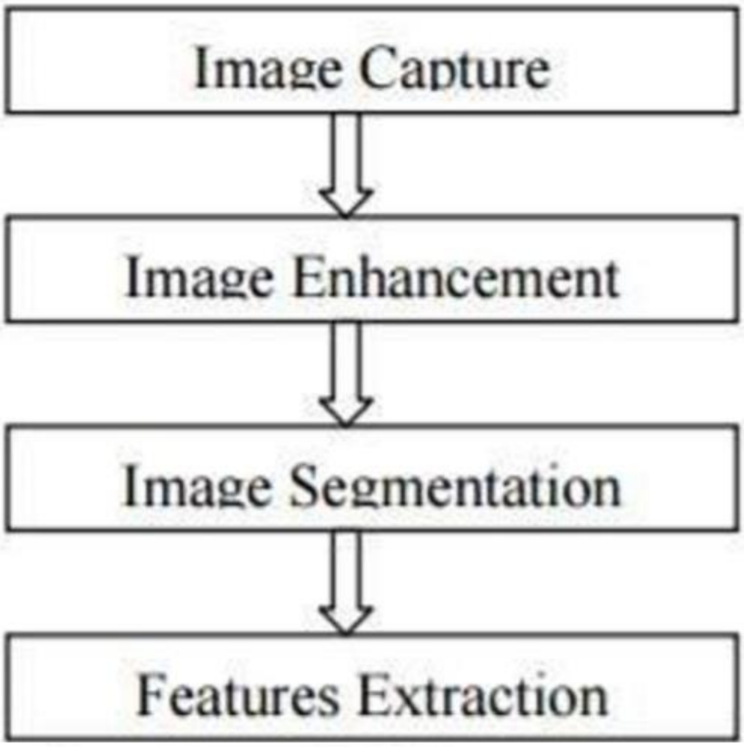
Perimeter = P = (Pi,j , X edge[P] = i, Y edge[P] = j) where, X edge [] and Y edge[] are vectors represent the co-ordinate of the i^{th} and j^{th} pixel forming the curve, respectively.

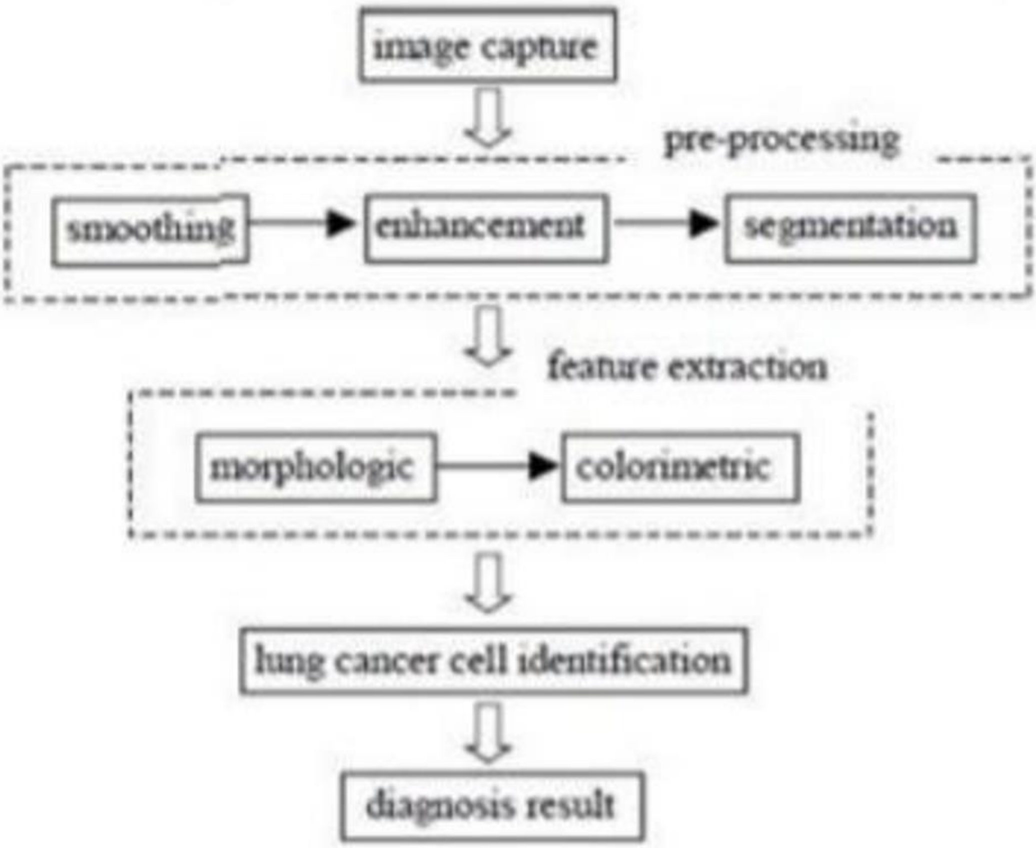
C) Eccentricity: This metric value is also called as roundness or circularity or irregularity complex (I) equal to 1 only for circular and it is less than 1 for any other shape. Eccentricity = Length of Major Axis /Length of Minor Axis

LITERATURE SURVEY AND REVIEW

Biomedical Image Processing is a growing and demanding field. It comprises of many different types of imaging methods likes CT scans, X-Ray and MRI. These techniques allow us to identify even the smallest abnormalities in the human body. The primary goal of medical imaging is to extract meaningful and accurate information from these images with the least error possible. Out of the various types of medical imaging processes available to us, MRI is the most reliable and safe. It does not involve exposing the body to any sorts of harmful radiation. This MRI can then be processed, and the tumor can be segmented. Tumor Segmentation includes the use of several different techniques. The whole process of detecting brain tumor from an MRI can be classified into four different categories: Pre-Processing, Segmentation, Optimization and Feature Extraction.

METHODOLOGY



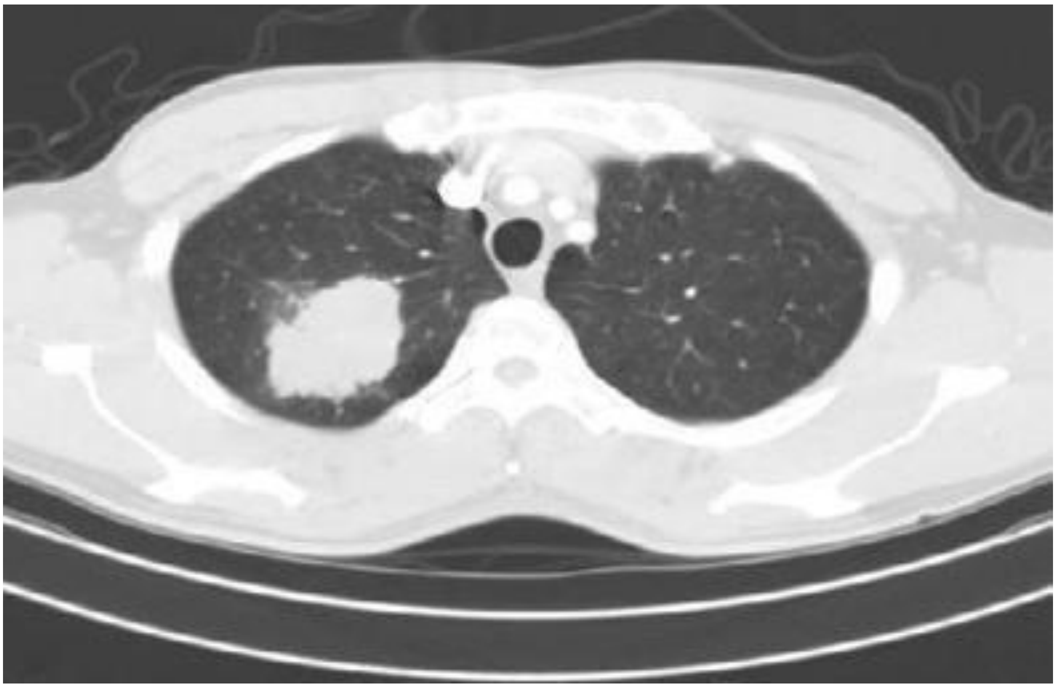


SYSTEM IMPLEMENTATION

```
 clc; clearvars;
close all; file =
'ok2.jpg'; imtool
close all;
FontSize = 12;
initImage = imread(file); [rows,
columns] = size(initImage); initImage =
rgb2gray(initImage); initImage =
medfilt2(initImage,[10 10]);
[B, A] = imhist(initImage)
C=A.*B;
D=A.*A; E=B.*D; n=sum(B);
Mean=sum(C)/sum(B);
var=sum(E)/sum(B)-Mean*Mean; std=
(var)^0.5; thresholdValue =
Mean+0.5*std; bwImage = initImage >
thresholdValue; figure
imshow(bwImage) title('binary
image');
img_dil = imdilate(bwImage , strel('arbitrary', 20));
figure imshow(img_dil); title('dilated image');
bwImage = imerode(img_dil , strel('arbitrary', 20 ));
figure imshow(bwImage); title('eroded image');
bigMask = bwareaopen(bwImage, 2000); finalImage =
bwImage; finalImage(bigMask) = false;
bwImage=bwareaopen(finalImage,55); figure
imshow(bwImage)
labeledImage = bwlabel(bwImage, 8);
RegionMeasurements = regionprops(labeledImage, initImage,
'all');
Ecc = [RegionMeasurements.Eccentricity]; RegionNo =
size(RegionMeasurements, 1); allowableEccIndexes =
(Ecc< 0.98); keeperIndexes =
find(allowableEccIndexes); RegionImage =
ismember(labeledImage, keeperIndexes);
bwImage=RegionImage; figure imshow(RegionImage)
%%%%% clear labeledImage;
clear RegionMeasurements;
clear RegionNo;
labeledImage = bwlabel(bwImage, 8);
RegionMeasurements = regionprops(labeledImage, initImage,
'all'); figure
imshow(initImage);
```

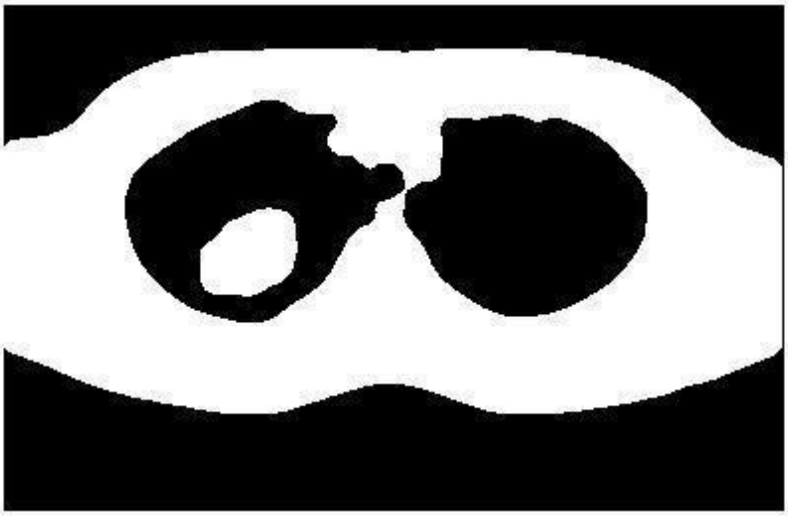
```
title('Outlines', 'FontSize', FontSize);
axis image; hold on;
boundaries = bwboundaries(bwImage);
numberOfBoundaries = size(boundaries, 1);
for k = 1 : numberOfBoundaries thisBoundary
= boundaries{k};
plot(thisBoundary(:,2), thisBoundary(:,1), 'r', 'LineWidth',
3); end
hold off;
RegionMeas = regionprops(labeledImage, initImage, 'all');
RegionNo = size(RegionMeas, 1);
textFontSize = 14; labelShiftX
= -7;
RegionECD = zeros(1, RegionNo);
%fprintf(1,'Region number Area Perimeter Centroid
Diameter\n'); for k = 1 : RegionNo
RegionArea = RegionMeas(k).Area;
RegionPerimeter = RegionMeas(k).Perimeter;
RegionCentroid = RegionMeas(k).Centroid; RegionECD(k)
= sqrt(4 * RegionArea / pi);
fprintf(1,'#%2d %11.1f %8.1f %8.1f %8.1f % 8.1f\n', k,
RegionArea, RegionPerimeter, RegionCentroid, RegionECD(k));
text(RegionCentroid(1) + labelShiftX, RegionCentroid(2),
num2str(k), 'FontSize', textFontSize, 'FontWeight', 'Bold');
end
```

Result and Summary

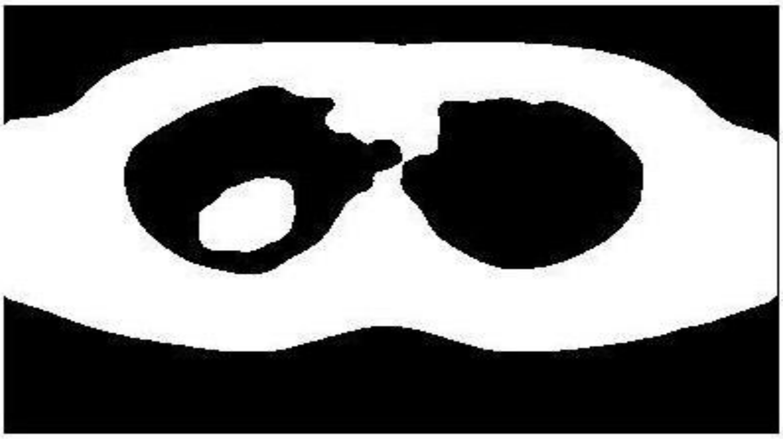


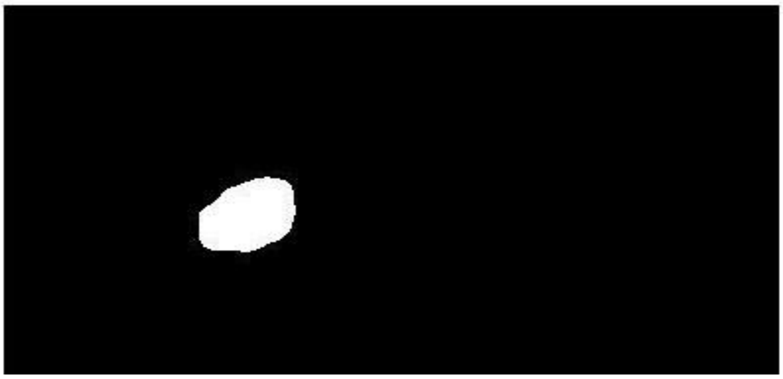
ORIGINAL IMAGE

binary image

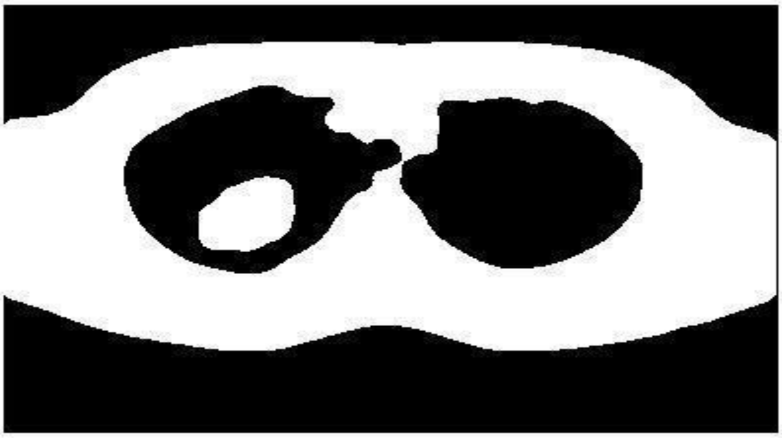


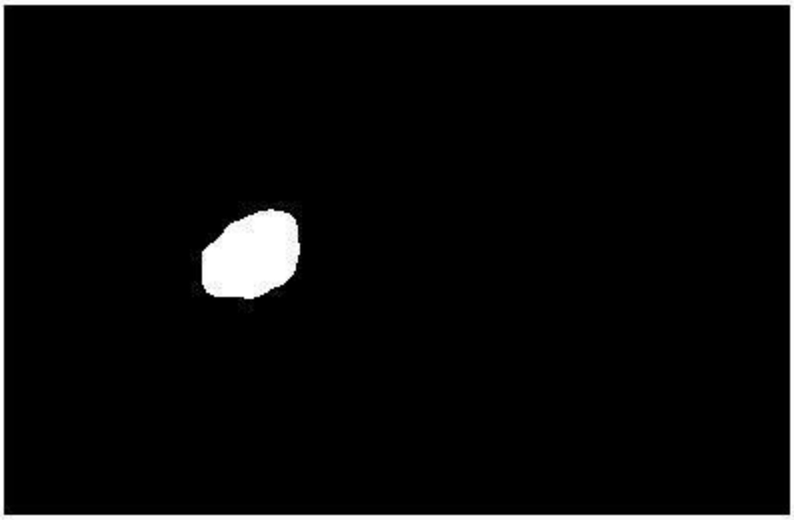
dilated image



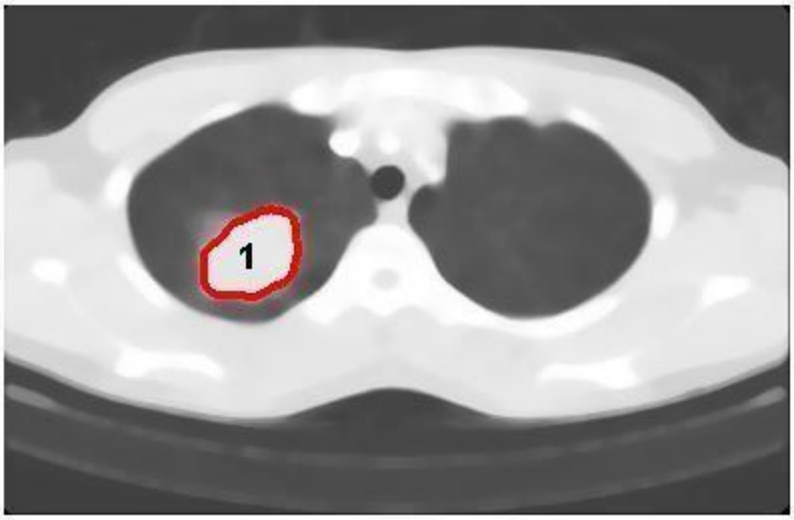


eroded image





Outlines



CONCLUSION

An image improvement technique is developing for earlier disease detection and treatment stages; the time factor was taken in account to discover the abnormality issues in target images. Image quality and accuracy is the core factors of this project, image quality assessment as well as enhancement stage where were adopted on low pre-processing techniques based on Gabor filter within Gaussian rules. The proposed technique is efficient for segmentation principles to be a region of interest foundation for feature extraction obtaining. The proposed technique gives very promising results comparing with other used techniques. Relying on general features, a normality comparison is made. The main detected features for accurate images comparison are pixels percentage and mask-labeling with high accuracy and robust operation. Thus using the above image processing techniques, we are able to find and detect tumors before they become cancerous.

Future Work

New techniques, having high sensitivity and specificity, are being developed in the medical image-processing field for better evaluation of lesions. Sophisticated image-analysis software is needed for quantitative measurement in medical imaging. Commercially provided image-processing packages often have limited functionality and frequently lack the validation that is essential before clinical usage.

With expansion in the size and quantity of medical images, computers have become indispensable for expediting processing and analysis. Computer algorithms for the depiction of anatomical structures and regions of interest (ROI) are vital for facilitating and automating specific radiological assignments. These algorithms, called segmentation and texture analysis algorithms, play a vital role in medical imaging.

Texture analysis is an image-processing technique by which different regions of an image are located based on their unique texture properties. This process plays an important role in many biomedical applications. In the pioneering work by Schad, brain tumours tissues were characterized by texture analysis based on the gray-level distribution, the gradient distribution, the gray-level co-occurrence matrix, and the gray-level run-length histogram. The classification and segmentation is carried out by a set of discrimination rules formed by the knowledge-based expert system. However, the system proposed by them was time consuming and could be used for only selected ROI. Kjaer *et al*. also carried out texture analysis for quantitative brain tumour tissue characterization and segmentation. In their study, texture images were computed from calculated T1 and T2 parameter images by applying groups of common first-order and second-order gray-level statistics. However, they were unable to achieve any discrimination between benign and malignant tumour. Gibbs *et al*. performed morphological operation using thresholding, edge detection, and region growing. However, the approach was framed only to replace the existing manual methods and has similar performance. Herlidou-Meme *et al*. carried out multivariate statistical analyses in order to discriminate each brain tissue type represented by its own set of texture parameters. In their study, texture analysis was initially performed on test objects to evaluate the method's dependence on acquisition parameters. Each selected brain ROI was characterized with both its mean gray-level values and several texture parameters. On the other hand, Zou *et al*.

utilized three two-sample validation metrics against the estimated composite latent gold standard, which was derived from several experts' manual segmentations by an EM algorithm. In this study, the distribution functions of the tumor and control pixel data were parametrically assumed to be a mixture of two beta distributions with different shape parameters. They estimated the corresponding receiver operating characteristic curve, dice similarity coefficient, and mutual information over all possible decision thresholds. Based on each validation metric they further computed an optimal threshold via maximization.

Szczypinski *et al* developed 'MaZda,' a software package for 2D and 3D image-texture analysis. It furnishes a flawless way for quantitative analysis of image textures, and comprises computation of texture features, methods for feature selection and extraction, algorithms for data classification, and various data visualization and image segmentation tools. Kamalov *et al*.

demonstrated a Java-based application for tissue-section image analysis. Holli *et al* developed techniques to examine texture criteria for discriminating healthy breast tissue from breast cancer in breast MRI. The study aimed at identification of possible dissimilarities in the texture characteristics of histological types (lobular and ductal) of invasive breast cancer. Harrison *et al*.

also implemented a similar texture-based analysis tool for effective classification of multiple sclerosis lesions. Various other distinct image-processing ideas have also been proposed. However, all the studies have been on limited image sets; none are available for routine clinical use because of the difficulties in devising a prototype software that is sufficiently user-friendly to be used by clinicians in their daily practice.

The aim of this study was to develop a user-friendly DICOM-based image-processing software for automatic segmentation and grading of brain tumours in MR images; we called this software 'Prometheus.' Our software would also provide the option of implementing various image-processing tools on the MR images for further enhancement. This software has been developed in Visual C++. Net 2003 compiler. Microsoft® Foundation Class (MFC)-based visual C++ has been used for coding.

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