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Detection and Segmentation of Cancer Regions in Oral MRI images using ANFIS Classification Method

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Abstract: ***The detection of oral cancer is an important area of research in the literature today. About 82% of the patients are diagnosed at the early stage and 27% of the patients are diagnosed at the advanced stage. Early detection reduces the mortality rate of the patients. An automated approach is proposed to detect and segment the oral cancer in oral Magnetic Resonance Images (MRI). The quality of the image is improved using adaptive mean filter and enhanced using adaptive histogram equalization technique. The enhanced image is transformed using Gabor transform and the features of the oral image are extracted from this transformed image. These features are classified using ANFIS classification approach. Morphological approaches are used to segment the cancer region in the classified abnormal oral MRI images.***

Keywords: Oral, cancer, detection, enhancement, filtered image.

I. INTRODUCTION

Now-a-days cancer has become the most common prevailing diseases in the world and oral cancer is in the 2nd position that affects the people in India. This oral cancer occurs in tongue, buccal, oropharyns and lips. Among these various parts of the oral organs, oropharyns cancer is the severe one and it is otherwise known as malignant cancer. At present, there may be advanced treatments such as radiation and chemotherapy available. As per World Health Organization (WHO) report, the person affected by oral cancer die due to oropharyns cancer. This type of oral cancer may affect the oral areas such as lips, tongue and gum with palate. The early detection of this type of cancer can save the human life. Hence, there is a need for detection and identification of the oral cancer at an earlier stage. The Magnetic Resonance Image (MRI) scanning technique is applied for getting better images of the affected oral organs. Though this scanning procedure is simple, it is often affected by artifacts and blurness due to the soft movement of these organs during scanning process. Hence, a simple and an efficient methodology is proposed for detection and identification of the cancer regions in oral organs. The dental radiograph is used to screen the cancer regions in tongue and lip regions (where the cancer region is visible in direct manner) using radiography technique. It is unable to screen the linear cancer affected regions in oral areas.

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Hence, this paper proposes soft computing technique to screen the linear cancer affected regions in oral organs. Fig.1 (a) shows the normal oral image of the tongue region of the mouth. Fig.1 (b) shows the cancer affected oral image of the tongue region of the mouth.

(a) (b)

Figure 1 Oral images (a) Normal oral image (b) Cancer affected oral image

This paper is organized as: Section 2 states the various methods for screening the oral cancer in oral MRI images using different techniques. Section 3 proposes an efficient image processing techniques to screen the oral cancer in oral MRI images and section 4 discusses the simulation results of the proposed oral cancer detection method with conventional methods. Section 5 depicts the conclusion of this paper.

II. LITERATURE SURVEY

Muzakkir Ahmed et al. (2017) used firefly approach for the detection and classification of the cancer affected oral MRI images. The authors constructed expectation maximization matrix from the source oral MRI images for the classification of abnormal patterns. Further, the authors applied grey level thresholding technique to identify the cancer regions in oral images. Rajdeep Mitra et al. (2016) proposed oral cancer detection method for segmenting the cancer regions in oral MRI images. The authors derived texture features from the oral MRI images and classified using linear classification algorithm. The watershed segmentation algorithm was applied on the classified features to segment the cancerous regions in oral MRI images. Anuradha et al. (2012), proposed morphological watershed algorithm to detect and segment the cancer regions in oral images. The watershed segmentation algorithm and marker controlled watershed segmentation algorithm were implemented to classify abnormal oral MRI images in order to accurately detect and segment the cancer regions. The authors attained 85.2% segmentation accuracy by using watershed segmentation algorithm and 90.25% segmentation accuracy by using marker controlled watershed segmentation algorithm.

Ranjan Rashmi Paul et al. (2005) developed oral cancer detection and segmentation methodology for segmenting the cancer regions in oral images. The authors used wavelet based neural networks for the classification of oral images into normal or cancer affected oral images. The neural network classification results were compared with other classification techniques. Woonggyu Jung et al. (2005) applied optical coherence tomography technique on source oral MRI images in order to detect and classify the cancer regions. The authors fragmented the source oral MRI image for improving the classification rate with segmentation accuracy. They compared the effect of linear classification algorithms with non-linear classification algorithms. Ram et al. (2005) developed computer aided approach for detection and classification of the cancerous regions in oral MRI images. The authors classified the source oral MRI image into either normal or malignant epithelial lesions based on their level of cancer affected regions in oral MRI images.

III. METHODS

The proposed oral cancer detection and segmentation approach is depicted in Fig.2. This method consists of the following stages as preprocessing, enhancement, Gabor transform, feature extractions and classifications. The noises in the source oral images are detected and filtered using adaptive mean filter, and then the filtered image is enhanced using adaptive histogram equalization technique. The enhanced oral image is transformed into multi resolution image using Gabor transform and the features of the oral image are extracted from this transformed image. These features are classified using ANFIS classification approach.

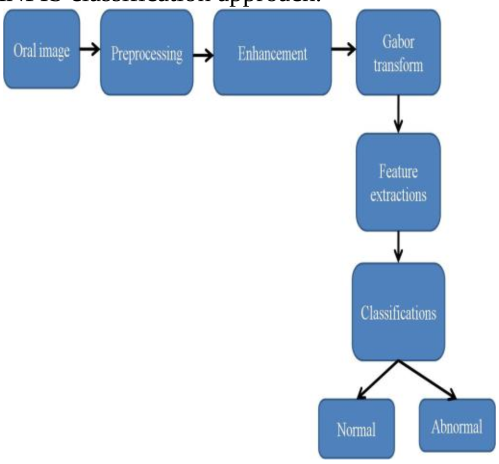
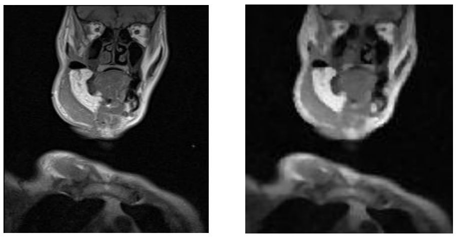


Figure 2 Proposed methodologies for cancer detection in oral images

A. Preprocessing

During image acquisition process the noise in the source oral image affects the automatic classification. Hence, these noises need to be removed in order to improve the classification detection accuracy. In conventional filtering methods such as mean and median filter, the noises in edge regions are affected while denoising filter is applied over the edges. This limitation is overcome by using adaptive filter which does not affect the edge pixels while denoising procedure is applied on the image. In this paper, adaptive median filter is used on the source oral image for detecting and removing the noise contents in an oral image as preprocessing technique. The source oral image and the denoised oral image are given in the Fig.3 (a) and Fig.3 (b), respectively.



(a) (b)

Figure 3 (a) Source oral image (b) Noise filtered oral image

B. Enhancement

The oral images captured using higher-end cameras are of low resolution images. Due to different abnormal patterns in oral images, the automatic classification process gets affected. In order to improve the grey level intensity of each pixel, adaptive local histogram equalization method is used on the filtered oral images. The following steps are used for adaptive histogram equalization process.

Step 1: Divide the filtered oral image into 8*8 non overlapping sub blocks.

Step 2: Compute histogram count on each divided non-overlapping blocks.

Step 3: Determine cumulative distribution on each computed histogram count.

Step 4: Replace cumulative distribution in each corresponding pixels in source oral images.

Step 5: Stop, when the end of the pixel in the source filtered oral image is reached.

Figure 4 Enhanced oral image

C. Gabor transform

The conventional Fourier Transform (FT) converts the spatial domain image into frequency domain image where there is no relationship of each pixel in its spatial domain. This limitation is overcome by implementing the Gabor transform which converts the spatial domain image into multi pixel image which relates each pixel in spatial, frequency and amplitude. The pixels in the enhanced oral images belong to spatial domain mode and hence cannot be used for direct feature extraction process.

Hence, the spatial domain oral image is converted using Gabor transform into multi resolution mode with respect to its frequency, orientation and amplitude components. The Gabor kernel is multiplied with enhanced oral image and it is given by,

$$G(x,y) = e^{\frac{-(x'^2 + \gamma^2 y'^2)}{2*\sigma^2}} * Cos\,(2*\pi*f*\frac{x'}{\lambda} + \varphi)$$

where, σ is the standard deviation and γ is the spatial aspect factor which is a constant set to 1 and λ is the spatial wavelength.

$$x' = x * cos\,\theta + y * sin\,\theta$$
$$y' = -x * sin\,\theta + y * cos\,\theta$$

The frequency of the Gabor kernel is represented by 'f' and it is varied from 1 to 5 with respect to spatial aspect factor. Hence, five numbers of Gabor kernels are produced by multiplying the Gabor kernel with Oral image with respect to different frequency. These Gabor multiplied images consist of real and imaginary terms. Further, Gabor magnitude image is constructed by selecting maximum pixel values at each position in the Gabor multiplied images (Y(x,y)) using the following equation.

$$Y(x,y) = I\,(x,y) * G(x,y)$$

where, the oral image is represented by $I\,(x,y)$ and Gabor kernel is represented by $G(x,y)$ and the output response of the Gabor multiplication is represented by $Y(x,y)$.

$$Y(x,y) = \sqrt{Real(Y(x,y)^2 + Imaginary\,((Y(x,y)^2}$$

The edges of the image remains smoothed and the quality of the image remains clear.

The response of Gabor transform is depicted in Fig.5.

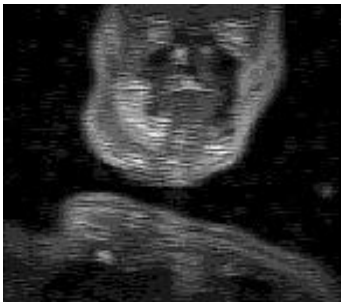


Figure 5 Gabor magnitude oral image

D. Feature Extractions

Features are the characteristics of the objects in an image used to differentiate one object from other objects in an image. The features are classified into generic and unique based on the properties. The generic features are the common features which cannot be used for detecting or classifying the small objects in an image. The unique features are the individual properties of the objects in an image and each object in an image may have distinct features. Hence, instead of generic features unique features like LBP (Local Binary Pattern) and GLCM (Gray-Level Co-Occurrence Matrix) extracted from the Gabor transformed magnitude oral image are used. They are explained in the following section.

LBP

It is one type of texture features used to classify the various regions in a Gabor transformed magnitude image. It encodes a feature value of each pixel in a Gabor magnitude oral image. The 3*3 window is placed on the Gabor transformed oral image and it computes LBP for each pixel using its surrounding pixels.

It is defined in the following equation,

$$LBP = \sum_{p=0}^{P-1} s(I_p - I_c) * 2^p$$

Here , I_p is the surrounding pixel over center pixel I_c and p is the number of surrounding pixels in 3*3 sub window. 's' is the functional factor defined as

$$s(x) = \begin{cases} 1; x \geq 0 \\ 0; x < 0 \end{cases}$$

The size of Gabor magnitude oral image and its extracted LBP image are the same and the extracted LBP feature image is depicted in Fig.6.

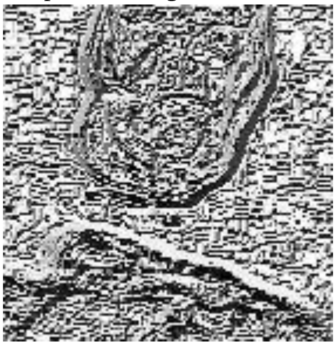


Figure 6 LBP extracted oral image

GLCM

The statistical features are computed with respect to any one of the following orientations as 0^0, 45^0, 90^0 and 135^0. The GLCM matrix is constructed at 45^0 orientations. The features Contrast, Homogeneity, Entropy, Angular Second Moment and Correlation are extracted from the GLCM.

$$Contrast = \sum_i \sum_j (i-j)^2 * G(i,j)$$

$G(i,j)$ are the elements in GLCM matrix with respect to its row (i) and column (j). The length of rows and columns remains the same in constructed GLCM matrix.

$$Homogeneity = \sum_i \sum_j \frac{1}{1+(i-j)} * G(i,j)$$

$$Entropy = -\sum_i \sum_j G(i,j) * ln\,G(i,j)$$

$$Angular\ Second\ Moment = \sum_i \sum_j G^2(i,j)$$

$$Correlation = \sum_i \sum_j G(i,j) * \frac{(i-\mu x)*(1-\mu y)}{\sigma x * \sigma y}$$

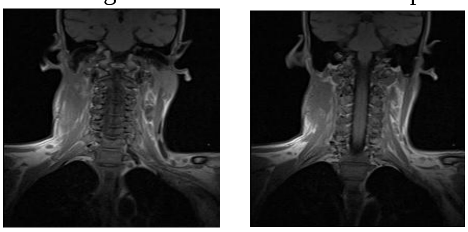
Here, σx and σy are the standard deviations of the constructed GLCM defined in the following equations.

$$\sigma x = \sqrt{\sum_i \sum_j (i-\mu x)^2 * G(i,j)}$$

$$\sigma y = \sqrt{\sum_i \sum_j (i - \mu y)^2 * G(i,j)}$$

E. Classification

Classification is the process of identifying whether source oral image is normal or cancer affected one. In conventional methods, Support Vector Machine (SVM) and Neural Networks (NN) are used for classifying the oral images to segment the cancer regions. The classification rate of the conventional method is not optimum and hence there is a need to improve the classification rate. ANFIS classification approach is used for classifying the oral image into either normal or cancer affected one. The ANFIS classifier receives the input from the extracted features of both normal and cancer affected oral images in training mode. The classification accuracy is improved by training more number of normal and cancer affected oral images. The ANFIS classifier has five number of internal layers with each layer consists of 12 number of neurons which can be initialized after several trails. The extracted features of LBP and GLCM are given as input to the ANFIS classifier in classification mode. The classification mode also receives the training pattern which consists of trained normal and cancerous images. The classification mode of the ANFIS classifier produces binary response as either 0 or 1, where 0 represents the normal oral image without abnormal pixels in it and 1 represents the abnormal oral image which contains abnormal pixels.



(a) Normal oral images

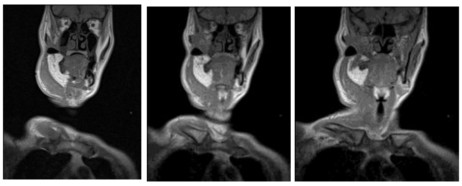
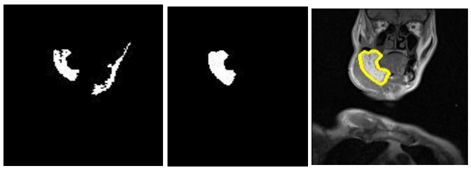


Figure 7 (b) Abnormal cancer affected oral images

F. Segmentation

The cancer region in the classified abnormal oral image is detected and segmented using morphological processing method. In this method, the process of dilation is employed on the abnormally classified oral image and its dilated response image. Further, erosion process is employed on the abnormally classified oral image and its eroded response is shown in Fig. 8 (a). The dilation and erosion functions are implemented on the classified abnormal oral image with structuring element 2. The morphological processing has the advantage of reducing over segmentation. The eroded oral image is subtracted from the dilated oral image and its response is shown in Fig. 8(b). The cancer region overlay in source oral image is shown in Fig. 8 (c).



(a) (b) (c)

Figure 8

(a) ROI image (b) Morphologically processed image (C) Cancer region segmented image

IV. RESULTS AND DISCUSSIONS

The automated cancer region identification and segmentation approach on oral images is applied on the oral images. The performance measure of the proposed segmentation of oral images using classification method is evaluated in terms of sensitivity (Se), specificity (Sp) and accuracy(Acc). These performance evaluation metrics are given in the following equations.

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

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

$$Accuracy\ (Acc) = \frac{TP + TN}{TP + TN + FP + FN}$$

The number of correctly detected cancer pixels in classified abnormal oral image is noted by True Positive (TP), the number of correctly detected non- cancer pixels in classified abnormal oral image are noted by True Negative (TN). The number of incorrectly detected cancer pixels in classified abnormal oral image is noted by False Positive (FP), the number of incorrectly detected non- cancer pixels in classified abnormal oral image are noted by False Negative (FN).

Table 1 Performance evaluation of oral cancer segmentation

Oral image sequences	Se (%)	Sp (%)	Acc (%)
1	91.6	89.7	92.1
2	90.7	93.2	93.6
3	92.1	94.1	92.1
4	89.8	91.3	93.7
5	92.1	90.7	94.6
6	91.9	92.6	95.1
7	90.6	91.5	96.6
8	89.7	90.8	95.8
9	91.3	92.9	96.1
10	92.5	93.1	95.7
Average	**91.2**	**91.9**	**94.5**

Table 1 shows the performance evaluation of oral cancer segmentation using ANFIS classification method and it achieves 91.2% of sensitivity, 91.9% of specificity and 94.5% of oral cancer segmentation accuracy. Table 2 shows the comparisons of proposed oral cancer segmentation with Muzakkir Ahmed et al. (2017), Anuradha et al. (2015) and Konstantinos et al. (2012).

Table 2 Comparison of proposed oral cancer segmentation

Authors	Muzakkir Ahmed et al. (2017)	Anuradha et al. (2015)	Konstantinos et al. (2012)	Proposed work in this paper
Methodologies	Thresholding technique	Watershed segmentation algorithm	Decision Support System	ANFI classifier
Se (%)	86.5	89.1	89.9	91.2
Sp (%)	88.4	89.9	87.5	91.2
Acc (%)	90.4	91.2	90.3	94.5

From, Table 2, it is clear that the proposed oral cancer segmentation method achieves high performance with respect to the performance evaluation parameters sensitivity, specificity and accuracy when compared with other methods.

V. CONCLUSIONS

This paper proposes oral cancer detection and segmentation method using Gabor transformed based ANFIS classification approach. The noises in the oral MRI image are removed and then it is enhanced using histogram equalization method. Then, the Gabor transform is applied on the enhanced oral MRI image and then LBP and GLCM features are extracted. These features are now trained and classified using ANFIS classification approach. The performance evaluation of oral cancer segmentation using ANFIS classification method achieves 91.2% of sensitivity, 91.9% of specificity and 94.5% of oral cancer segmentation accuracy.

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Prof Dr G Arumugam served as Professor and Head in the Department of Computer Science, School of Information Technology, Madurai Kamaraj University for 23 years. He had his Master degree in Applied Mathematics from P S G College of Technology, Coimbatore , Tamil Nadu, India specializing in Computer Science(1978-80) and obtained his PhD in Applied Mathematics (Numerical Analysis-Specialization)(1984-87) from the University of Pierre and Marie Curie, Paris ,France and INRIA, Paris, France. His area of interest is design and analysis of Algorithms and worked in the areas of Graph algorithms, Cryptography and Network Security, Data Mining and Image Processing. He had software industry experience as Project Manager in Hexaware Information Systems, Chennai and as Consultant, Polaris Software Ltd, Chennai. He had been a Post Doctoral Fellow in the University Jyvaskyla, Jyvaskyla, Finland and Visiting Lecturer in the Ngee Ann Polytechnic, Singapore in the School of Information and Communication Technology. He was awarded French Government Scholarship to carry out his research in Paris ,France in the area of Applied Mathematics in 1984-1985. M.PraveenaKirubabai is an Associate Professor in Computer Science at Lady Doak College, Madurai, Tamil Nadu, India. She received her Master's degree in Computer Applications from Madurai Kamaraj University, India, and is currently pursuing DDoctoral Research in Madurai Kamaraj University, Madurai, India. Her current research areas include Image Processing and Data Mining.

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