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Full Length Research Article

HISTOGRAM FEATURES OF OSMF IMAGES FOR CLASSIFICATION BY AANN

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ABSTRACT

Oral Submucous Fibrosis (OSMF) is an insidious chronic progressive precancerous condition of the oral cavity and oropharynx with a high degree of malignant potential. It is a precancerous condition associated with the use of areca nut in various forms. there is a progressive inability to open the mouth and tongue movement gets restricted to varying degrees depending up on the severity of the disease process thus it becomes essential to intervene the disease at an early stage to avoid progression to cancer. histopathological investigations are the gold standards for diagnosis , but subjective variations are always problematic. Computer aided classification with image analysis techniques are on the research line already with some positive outcomes this research has attempted to classify osmf microscopic images with aann classiffer by using histogram features

INTRODUCTION

Early detection of premalignant and cancerous mucosal lesions improves the survival and morbidity of patient's sufferings *(*Shilpa *et al*., 2012*)*. Currently one of the greatest challenges to oral oncobiologists is to determine and identify the degree of tissue damage or stages of various precancerous states of oral tissue and to detect the exact transition of a normal tissue to precancerous state *(*Sanjit Mukherjee *et al*., 2010*)*. Traditionally, the pathologists use histopathological images of biopsy tissue and examined them under light microscope to detect OSMF which is a highly qualitative process *(*Joel B. Epstein *et al*., 2008*)*. Oral Submucous Fibrosis (OSMF) is a precancerous condition associated with the use of areca nut in various forms. Worldwide, estimates of OSMF shows a confinement to Indians and Southeast Asians, with overall prevalence rate in India to be about 0.2% to 0.5%. Ingestion of chillies, genetic susceptibility, nutritional deficiencies, altered salivary constituents and autoimmunity and collagen disorders may be involved in the pathogenesis *(*Rajendran, 2009*)*. The condition is well recognized for its malignant potential rate of 7.6% and is particularly associated with use of areca nut in various forms with significant duration and frequency of chewing habits.

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In OSMF, there is a progressive inability to open the mouth and tongue movement gets restricted to varying degrees depending up on the severity of the disease process *(*Mitesh Amitkumar Modi *et al*., 2005*)*. Fig. 4.2 shows the microscopic image of OSMF. Atrophic epithelium with loss of retepegs and dense fibrous connective tissue are seen. Presently, no specific diagnostic test is available for OSMF except for histopathological studies. The main histopathological characteristic of OSMF is the deposition of collagen in the subepithelial connective tissue leading to epithelial atrophy. It has been found that exposure of buccal mucosal fibroblasts to alkaloid may result in the accumulation of collagen. Collagenase activity has been found to be lower in OSMF than in normal oral mucosa. These findings suggest that OSMF should be considered as a collagen metabolic disorder resulting from alkaloid exposure and individual variations in collagen metabolism. Outcomes of OSMF are characterized by two features: the persistence of the disease and its potential to become malignant. OSMF is strongly associated with a risk of oral cancer *(*Sanjit Mukherjee *et al*., 2010*)*. OSMF has been graded by many pathologists based on clinical features or histopathology or both. It has been graded into Grades I, II and III based on the microscopic features. Initially, OSMF lesions are characterized by a few epithelial and inflammatory changes in the connective tissue and subsequently as the disease progresses, fibrosis and later hyalinization with less vascularity occur.

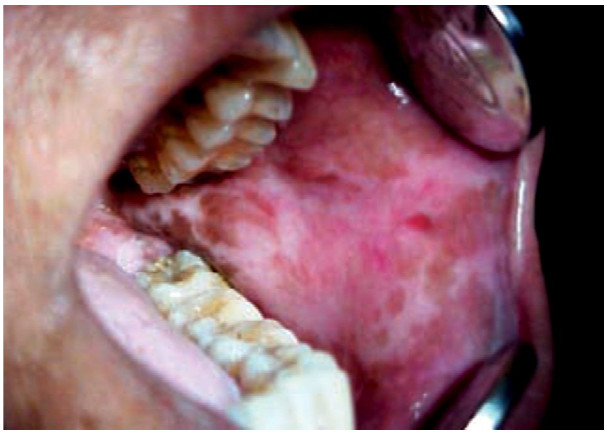


Fig. 4.1. Intraoral photograph of the buccal mucosa showing blanched oral mucosa with erosions in the initial stages of oral submucous fibrosis

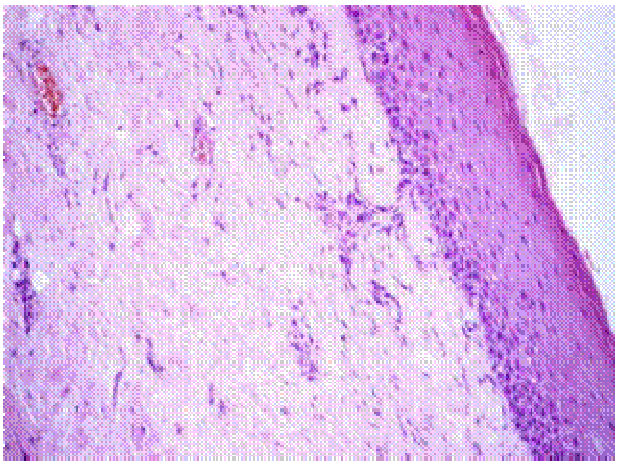


Fig. 4.2. Microscopic image of OSMF showing an atrophic epithelium and fibrous connective tissue; E-Epithelium; CT-Connective Tissue; K-Keratin

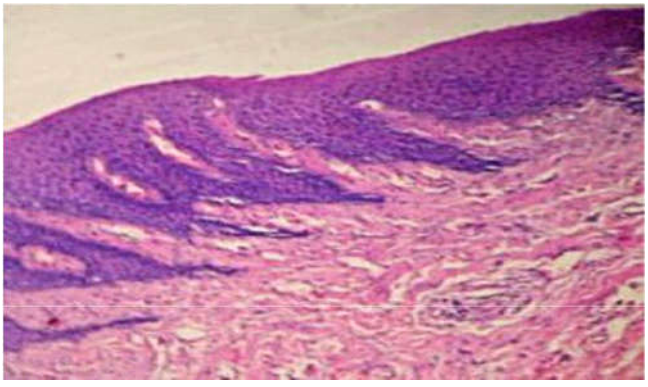
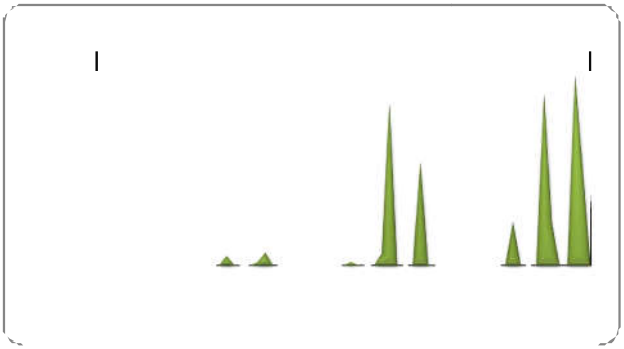


Fig. 4.3. (a) Normal Microscopic Image (b) Histogram of Normal Microscopic Image given in (a)



The simple pathological evaluation procedure currently used does not provide a quantitative analysis of the vital changes in the tissues; that is, epithelial dysplastic changes, subepithelial fibrosis (Fernando Augusto *et al*., 2009). Thus a computer based diagnostic approach will enhance the accuracy of diagnosis as well as may assist in grading OSMF (Rusha Patra *et al*., 2012).

Related Work

Application of Image Analysis methods in OSMF, other precancerous conditions and oral cancer for diagnosis, staging and classification aspects is being expertise in the recent years. In June 2013, Anuradha K and Sankaranarayanan K described feature extraction techniques to classify oral cancers using Image Processing (Joel B. Epstein *et al*., 2008). In this work, a system is developed to segment, extract features and classify cancers. Later, a comparison is made. The proposed system consists of five steps. First, the images are enhanced and the Region of Interest (ROI) is segmented using Marker Controlled Watershed Segmentation.

Feature Extraction methods like Gray Level Co-occurrence Matrix (GLCM), Intensity Histogram and Gray Level Run Length Matrix (GLRLM) are used to extract features from ROI. Next, classification is made using Support Vector Machine (SVM) classifier to classify the tumor as benign or malignant mass and a comparative study is performed to identify the best feature extraction technique. In August 2012, Mitesh Amitkumar Modi, Vishal R. Dave, Viral G. Prajapati and Keyur A.Mehta described "A A Clinical Profile of Oral Submucous Fibrosis" (Sanjit Mukherjee *et al*., 2010). A hospital-based study was conducted on 80 oral Submucous Fibrosis cases who visited our hospital in Jamnagar. A detailed history of each patient was recorded along with a clinical examination. Biopsy was performed for histopathological correlation. Clinical stage of the disease in terms of the ability to open one's mouth was correlated with histopathological grading.

Features for osmf classification

Color histogram features: The histogram of a digital image with gray levels in the range (0, L−1) is a discrete function, where L is the number of discrete gray level

$$P(rk)=^{n}k ,0<k<L-1 \quad (4.1)$$

where r_k is the k^{th} gray level, n_k is the number of pixels in the image with that gray level, n is the total number of pixels in the image with k = 0, 1, 2, .., L − 1. In short, $P(r_k)$ gives an estimate of the probability of occurrence of gray level r_k. The technique used for obtaining a uniform histogram is known as histogram equalization or histogram linearization.

The steps to perform histogram equalization are

- Find the probability of occurrence of each gray level (r_k) in the input image
- Use the transformation function $s_k = T(r_k)$ to obtain the histogram equalized image. Histogram equalization significantly improves the visual appearance of the image.

The feature is defined as a function of one or more measurements, each of which specifies some quantifiable property of an object, and is computed that it is quantifying some of the important characteristics of the object (Duda, 2000). Feature selection helps to reduce the feature space which improves the prediction accuracy and minimizes the computation time. Quantitative evaluation of histopathological features is not only vital for precise characterization of any precancerous condition but also crucial in developing automated computer aided diagnostic system (Muthu Rama Krishnan, 2009). Sub- epithelial hyalinization and fibrosis are characteristic histological features of OSMF. In this research work, color histogram features were extracted from both normal and OSMF microscopic images. Histogram construction has already been explained in detail in a previous work published by the same author, on OSMF (Venkatakrishnan, ?).

Four fold cross validation: In this research work fou fold cross validation is carried out. In four fold cross validation the dataset with 200 images consists of 100 normal microscopic images and 100 affected microscopic images is divided into four equal size sub samples. Out of the four sub samples, a single sub sample is retained as the validation data for testing the model and the remaining samples were used as the training data. Cross validation process was repeated four times and performance of the system was analyzed. In four fold cross validation, the training set is randomly divided into 4 disjoint sets namely fold1 ($f1$), fold2 ($f2$), fold3 ($f3$), fold4 ($f4$), where each fold having same number of data values. These folds are formed with the following grouped folders namely gfi (i=1, 2, 3, 4) = $\sum f_j$ (training data) in which f_i is tested against training data. Table 4.1 shows the four fold cross validation of data organized for training and testing for classification.

Table 4.1. Four fold cross validation

1	2	3
Grouped Folder No.	Training Data	Test Data
gf1	$f2+f3+f4$	$f1$
gf2	$f1+f3+f4$	$f2$
gf3	$f1+f2+f4$	$f3$
gf4	$f1+f2+f3$	$f4$

Further a total of 200 images with 100 normal microscopic images and 100 OSMF affected microscopic images are collected and used for training and testing. The 200 microscopic images are (i= 1, 2, 3, 4) divided into four folds, namely f_i. Each fold (f_i) contains 50 microscopic images.

Experimental results

A total of 200 microscopic images which consists of 100 OSMF images and 100 normal images are considered. For four fold cross validation training data gf_i (i=1,2,3,4) consisting of 150 microscopic images (50 images (25 Normal + 25 OSMF) + 50 images (25 Normal + 25 OSMF) + 50 images (25 Normal + 25 OSMF)) are used. For testing, 50 microscopic images (25 normal and 25 OSMF) are used.

Evaluation using AANN

AANN models perform an identical mapping of the input space (Abdul Jaleel, 2012).

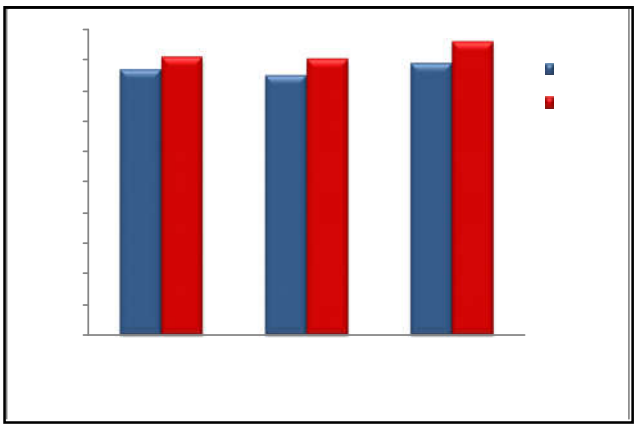
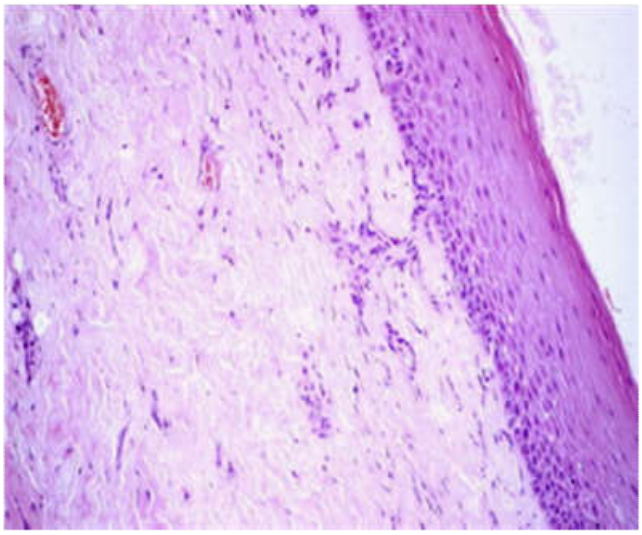


Table 4.4: Average performance of normal and OSMF classification by

AANN model using Histogram features

Structure of AANN	Accuracy (%) Feature vector dimensions (No. of bins)					
	16		32		64	
	Normal	OSMF	Normal	OSMF	Normal	OSMF
16L 76N 2N 76N 16L	87.0	88.0	87.0	89.0	72.0	78.0
32L 76N 4N 76N 32L	88.5	89.5	91.5	95.0	82.5	85.0
64L 128N 6N 128N	88.5	90.7	92.0	94.5	93 .0	95.0



The distribution of 16, 32 and 64 dimensional feature vectors in the feature space for different bins is captured using an AANN model. Separate AANN models are used to capture the distribution of feature vectors of each class and the network is trained for 500 epochs(10). One epoch of training is a single presentation of all the training vectors to the network. For evaluating the performance of the system, the feature vector is given as input to each of the models. The output of the model is compared with the input to compute the normalized squared error. The normalized squared error (E) for the feature vector y is given by E where

$$\frac{\|y-o\|^2}{=\|y\|^2}$$

, where

o is the output vector given by the model. The error (E) is transformed into a confidence score (C) using C = exp (−E) × 100. The average confidence score is calculated for each model.

The class is decided based on the highest confidence score. The classification results for the different bins are shown in Fig. 4.7. The performance of the system is evaluated, and the method achieves 95.0% for classification rate for 64 bins. The structure of AANN model plays an important role in capturing the distribution of the feature vectors. After some trial and error, the network structure 64L - 128N - 8N -128N - 64L is obtained. This structure seems to give good performance in terms of classification accuracy. The number of units in the third layer (compression layer) determines the number of components captured by the network. The AANN model projects the input vectors onto the subspace spanned by the number of units (n_C) in the compression layer. If there are n_C units in the compression layer, then the histogram feature vectors are projected onto the subspace spanned by n_C components to realize them at the output layer.

The effect of changing the value of $\mathbf{n_C}$ on the performance of OSMF classification is studied. There is no major change in the performance if $\mathbf{n_C}$ is between 4 and 6 and the performance of the system decreases if it is less than 2 or more than 6. The decrease in the performance for $\mathbf{n_C}$< 2 indicates that there may not be a boundary between the components representing the microscopic image information.

The decrease in the performance for $\mathbf{n_C}$> 6 indicates that the training data may not be sufficient for capturing the distribution of feature vectors. The results are shown in Table 4.4 and maximum performance is obtained with the structure 64L - 128N - 8N - 128N - 64L as shown in Fig. 4.7. Similarly, the performance is obtained by varying the number of units in the expansion layer keeping the number of units in the compression layer to 4. When the number of units in the expansion layer is increased from 128 to 146, there is no considerable increase in the performance.

DISCUSSION

OSMF being a PMD(potentially malignant disorder) with a high risk of cancer formation needs appropriate diagnosis at the early stage this research work has proposed an AANN pattern classiffier with extracted histogram features with a considerable outcome already many research workers have experimented other classifiers in OSMF and the results had also been satisfied .In this work a maximum accuracy of 95% was achieved for the structure 64L-128N-8N-128N-64L.

Conclusion

This technique proves to be a reliable method to classify OSMF images in future more research works with other features could be attempted for better results.

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