ISSN: 2230-9926

Available online at http://www.journalijdr.com

IJDR

International Journal of Development Research
Vol. 07, Issue, 08, pp.14775-14778, August, 2017

REVIEW ARTICLE OPEN ACCESS

COMPARATIVE EVALUATION OF PATTERN BASED CLASSIFICATION OF LEUKOPLAKIA WITH BICC FEATURES BY GMM AND AANN CLASSIFIERS

***Dr. Venkatakrishnan, S.**

Assistant Professor, Mechanical Engineering, Engg-Wing DDE, Annamalai University

ARTICLE INFO

Article History:

Received 24th May, 2017
Received in revised form
15th June, 2017
Accepted 23rd July, 2017
Published online 30th August, 2017

Keywords:

Leukoplakia,
Classification,
AANN, GMM, BICC.

****Corresponding author***

ABSTRACT

Leukoplakia one of the common pre cancerous lesions possess a high risk of malignant transformation. This can be prevented if it is diagnosed and treated earlier. various available Histopathological investigations and molecular research works , attempts are also being made by computer analysts to find out a technique that could accurately diagnose and classify pre cancerous lesions, condition and oral cancer.in this work, BICC (Block Intensity Code Comparison) features were extracted from microscopic images of leukoplakia -affected mucosae and used for classification by GMM and AANN classifiers. The performance was evaluated and compared based on the sensitivity, specificity and accuracy of the results.

Citation: Dr. Venkatakrishnan, S. 2017. "Comparative evaluation of pattern based classification of leukoplakia with bicc features by gmm and aann classifiers", *International Journal of Development Research*, 7, (08), 14775-14778.

INTRODUCTION

Oral cancer is one of the most dreadful cancers affecting humans with high mortality and morbidity rates (Paul, 2005) potentially malignant disorders (PMDs) pose a high threat of malignant transformation as compared to normal oral mucosa. leukoplakia is the most common PMD. it is diagnosed by exclusion of other similar white lesions such as oral lichen planus, leukoedema, white sponge nevus, etc. (Kramer *et al*., 1974) Leukoplakia is defined as a 'predominantly white lesion of the oral mucosa that cannot be characterized as any other definable lesion; some oral leuokoplakia will transform into cancer.' It may be homogenous or heterogenous and focal or disseminated in distribution (Rajendran, 2004). Homogenous lesions are regular, smooth and white surfaced whereas heterogenous are mixed with an erythematous component called erythroplakia which comparatively has higher risk of malignant transformation.

****Corresponding author:*** **Dr. Venkatakrishnan, S.,**
Assistant Professor, Mechanical Engineering, Engg-Wing DDE, Annamalai University.

Leukoplakia possesses 25% of malignancy risk, thus necessitates an accurate diagnosis and early management (Van der Waal, 2010). It has been proved that leukoplakia is more frequent in tobacco smokers than others. In addition, nutrition deficiencies, constant irritants have also been suggested as other etiological factors (Rajendran, 2009). Histopathological analysis of the tissue sections obtained from biopsies has been the only reliable method to diagnose precancerous and cancerous lesions. Dysplastic changes in the tissue sections of leukoplakia and other PMDs are graded as mild/moderate/ severe and thus the risk of transforming into oral cancer is assessed (Smoking and the mouth, 2000). Since such evaluation methods are highly subjective and hence end up in individual variations.

Computer analysis of images: Research works on computer applications in oral lesions had been done since 1970s (Kalaiselvi Geetha *et al*., 2009; Martorell-Calatayud *et al*., 2009; Gao, 1992).

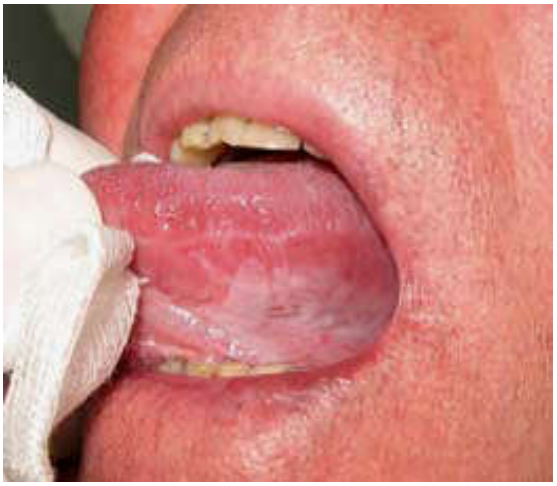

Fig.1. Homogenous Leukoplakia

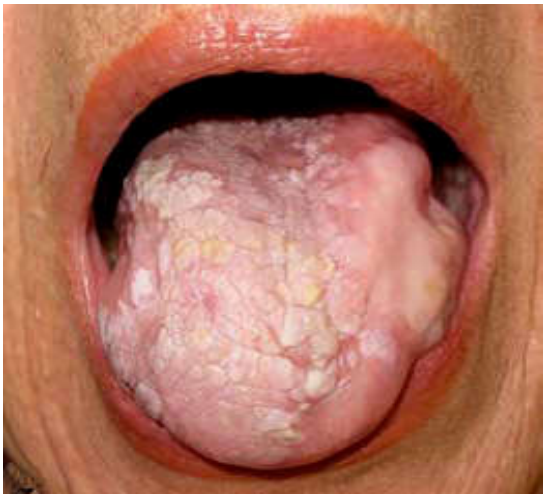

Fig.2. Heterogenous Leukoplakia

Numerous experimental attempts have Been done successfully on image analysis of oral cancer and OSMF (Tathagata Ray, 2005).Only a very few works have been done on leukoplakia (Muthu Rama Krishnan, 2011). With a motivation from the previous research works on image analysis of oral cancer and precancer, an attempt has been made in this research to classify normal mucosa and leukoplakia-affected mucosa using image analysis of BICC features extracted from those images (Shilpa,; Smitha *et al*., 2011; Rajendran *et al*., 2004). Photomicrograhc images of normal and leokoplakia affected mocosae were obtained from the department of Oral Pathology, Rajah Muthiah Dental College and Hospital. BICC features were extracted from the images.Pattern lassification was done using AANN and GMM. The leukoplakia affected mucosa shows a hyperkeratinised epithelium with mild dyplasia and a few inflammatory cells in the connective tissue.

Features for leukoplakia classification

BICC Feature Extraction

BICC features characterize the intensity variations between blocks in image. The intensity changes between blocks of a frame are represented by block intensity comparison code (5). To extract the BICC features, each image is divided into blocks of size KxK. Images of size 326 x 244 are used for experimental studies. BICC is computed as follows:

- Divide the frame into 5 x 5 blocks. (Fig.)
- Compute the average intensity in each block.
- Compare the average intensity values of each block in an image with every block in the image.
- BICC is generated using the formula

$$Y(i-1)25+j-i(i+1) = \begin{bmatrix} 1 \text{ if } X \\ 2 \end{bmatrix} \begin{cases} (I) > X(J) \\ 0 \text{ otherwise,} \end{cases}$$

where $1 \le i \le 25$, $2 \le j \le 24$, $i < j$ and $x(i) > x(j)$ are the average intensities for the i^{th} and j^{th} blocks respectively

EXPERIMENTAL RESULTS

A total of 200 microscopic images which consists of 100 Leukoplakia 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 Leukoplakia) + 50 images (25 Normal + 25 Leukoplakia) + 50 images (25 Normal + 25 Leukoplakia)) are used. For testing, 50 microscopic images (25 Normal and 25 Leukoplakia) are used.

EVALUATION USING AANN

AANN models perform an identical mapping of the input space. The distribution of 10, 45 and 105 dimensional feature vectors in the feature space for different sized blocks of BICC feature vectors 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. 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

$\| y-o \|^2$

feature vector y is given by, $E = \| y \|^2$, where o is the output vector given by the model. The error (E) is transformed into a confidence score (C) using C = exp (−E). The average confidence score is calculated for each model. The class is decided based on the highest confidence score. The performance of the system is evaluated, and the method achieves 93.0% classification rate. 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 105L - 210N - 60N -210N - 105L is obtained. The structure seems to give good performance in terms of classification accuracy. For testing, the feature vectors extracted from the various classes are given as input to the model and the corresponding class has the maximum confidence score. The classification results for the different sized blocks of BICC feature vectors shown in Fig. 5.9. From the results, it is observed that the overall classification accuracy is 94.0 % for 105 BICC features. 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 BICC feature vectors are projected onto the subspace scanned by n_c

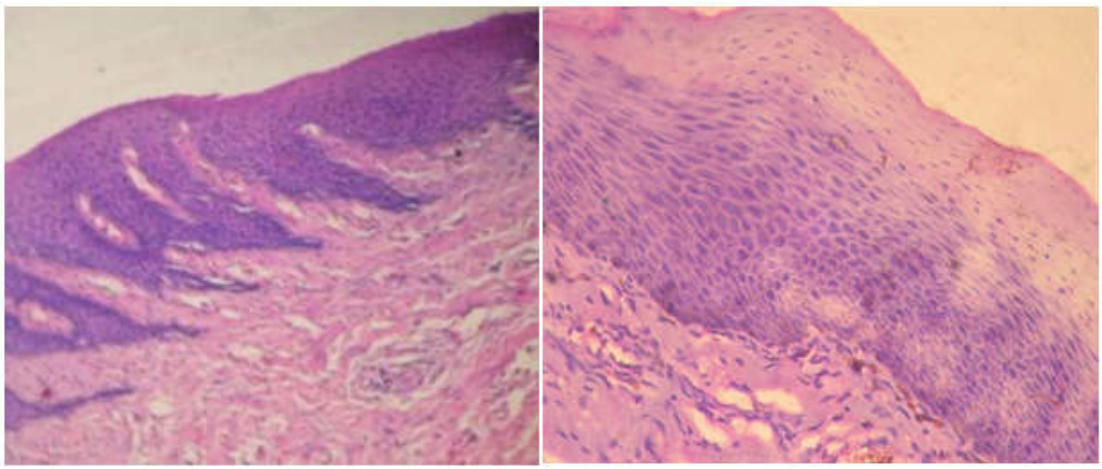

Fig. (a) Normal microscopic image (b) Leukoplakia microscopic image

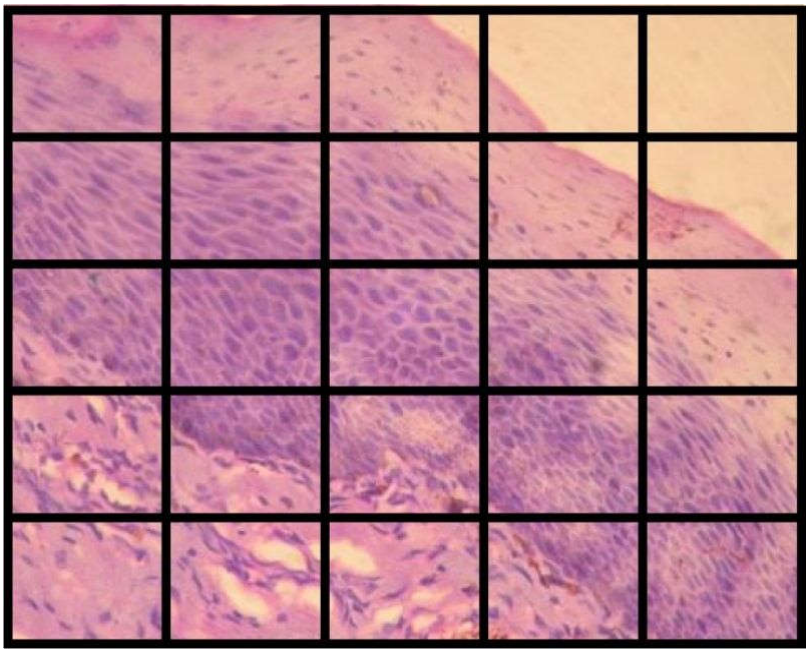

Fig. 5.5. Leukoplakia image divided into blocks of size 5 X 5

Table 5.3. Average performance of normal and Leukoplakia classification by AANN model using BICC features

Structure of AANN	Accuracy(%)					
	Feature vector dimensions (No. of BICC features)					
	10		45		105	
	Normal	Leukoplakia	Normal	Leukoplakia	Normal	Leukoplakia
10L - 12N - 3N - 12N - 10L	80.2	85.4	82.6	87.4	86.2	89.4
45L - 78N - 12N - 78N - 45L	85.4	89.4	87.2	90.1	89.6	93.4
105L - 210N - 60N - 210N - 105L	88.9	90.4	90.1	92.3	91.0	95.0

Table 5.4. Average performance of normal and Leukoplakia Classification by GMM model using BICC features

No. of mixtures	Accuracy (%)					
	Feature vector dimensions (No. of BICC features)					
	10		45		105	
	Normal	Leukoplakia	Normal	Leukoplakia	Normal	Leukoplakia
2	82.4	85.5	85.4	87.8	88.5	90.4
5	84.6	88.4	86.3	90.1	88.9	91.3
10	87.6	90.1	90.4	92.2	90.1	92.0

components to realize them at the output layer. Table 5.3 shows the performance of normal and Leukoplakia classification by AANN with BICC features and the maximum performance is achieved with the structure 105L - 210N - 60N - 210N - 105L as shown in Fig

Evaluation using GMM

Gaussian Mixture Models are a type of density models comprises a number of components which are combined to provide a multi-model density. The performance of the system is studied for a mixture of Gaussians varying from 2 to 10. When the number of mixtures are less, the performance is low. So the classification performance increases with the number of mixtures increases. The performance results for various mixtures and the maximum performance is achieved with the 10 mixtures as shown in Table 5.4.

DISCUSSION

BICC features were extracted from normal and leukopalkia images and classified with AANN and then GMM classifiers an accuracy of 95% was obtained with AANN for the structure 105L-210N-60N-210N-105L . in GMM classification the maximum accuracy was 92 % with 10 mixtures thus it is clear that AANN has a better performance than GMM in leukopalkia classification.

Conclusion

Both the pattern classifiers used in this research work seem to be reliable for lision classification. anyway more attempts should be made and experimented in the same area for improved accuracy and results.

REFERENCE

Byakodi R., Byakodi S., Kiremath S., Bya Kodi J., Adaki S., Marathe K. and Mahiral P. 2012. "Oral cancer in India: an epidemiologic and clinical review", *Journal of Community Health,* vol. 37, no. 2, pp. 316-319, April.

Gao S. 1992. "Cell morphometric analysis in oral submucous fibrosis, leukoplakia and squamous cell carcinoma", *Zhonghua Kou Qiang Yi Xue Za Zhi*, vol. 27, no. 3, pp. 145-147, May.

Kalaiselvi Geetha, M, Palanivel S. and Ramalingam V. 2009. "A novel block intensity comparison code for video classification and retrieval", *Expert Systems with Applications,* vol. 36, no. 3, pp. 6415-6420, April.

Kramer I. R. H, El-Labban N. G and Sonkodi S, "Further Studies On Lesions Of The Oral Mucosa using Computer-Aided Analyses Of Histological Features", *British Journal of Cancer*, vol. 29, p. 223, 1974.

Martorell-Calatayud A, Botella Estrada, Bayan Sebastian J. V, Sanmartin and Jimeney O. 2009. "Oral Leukoplakia: Clinical, Histopathologic and Molecular Features and Therapeutic Approach", *Actas Dermosifiliogr*, vol.100, pp. 669-684, October.

Muthu Rama Krishnan M, Acharya U. R, Chakraborty C and Ray A. K. 2011. "Automated Diagnosis of Oral Cancer Using Higher Order Spectra Features and Local Binary Pattern: A Comparative Study", *Twin Cities Radiation Therapists,* vol. 10, no. 5, pp. 391-504, October.

Paul R. R., Mukharjee A., Dutta P. K., Banarjee S., Pal M., Chatterjee J., Chaudhuri, K. and Mukherjee K. 2005. "A novel wavelet neural network based pathological stage detection technique for an oral precancerous condition", *Journal of Clinical Pathology*, vol. 58, pp. 932-938, September.

Rajendran R. and Sivapathasundaram, B. 2009. "*Shafer's Textbook of Oral Pathology*", 6thEdition, Elsevier India, 2009.

Rajendran, R. 2004. "Oral leukoplakia (leukokeratosis): Compilation of facts and Figs", *Journal of Oral Maxillofac Pathol*, vol. 8, pp. 58-68,.

Rajendran, R.2004. "Oral leukoplakia (leukokeratosis): Compilation of facts and Figs", *Journal of Oral Maxillofac Pathol*, vol. 8, pp. 58-68.

Shekhar Singh, 2012. "Cancer Cells Detection and Classification in Biopsy Image", *International Journal of Computer Applications,* vol. 38, no. 3, pp. 15-21, January.

Shilpa B. Rajesh and Satheesha B. H. Reddy, "Cytomorphometric Analysis of Obtained Squames Obtained from Normal Oral Mucosa and Lesions of Smitha T, Sharada P and Hc Girish, "Morphometry of the basal cell layer of oral leukoplakia and oral squamous cell carcinoma using computer-aided image analysis", *Journal of Oral Maxillofacial Pathology*, vol. 15, no. 1, pp. 26-33, January-April 2011

Smoking and the mouth; Quit Victoria Vic Health, "http://quitvictoriaichealthcom/smoking+and+the+mouth", 2000.

Tathagata Ray, M. E, Shivashankar Reddy D, Anirban Mukherjee, Jyotirmoy Chatterjee, Ranjan R. Paula and Pranab K. Dutta, 2008. "Detection of constituent layers of histological oral sub-mucous fibrosis: Images using the hybrid segmentation algorithm", *Oral Oncology*, vol. 44, no. 12, pp.1167-1171, December.

Van der Waal I. 2010. "Potentially malignant disorders of the oral and oropharyngeal mucosa; present concepts of management", *Oral Oncology*, vol. 46, no. 6, pp. 423-425, June.

****