

# Analysis of Leukoplakia Disease Classification using Radial Basis Function Neural Network

Dr. S. Venkatakrishnan <sup>#1</sup>, Dr. C. Kalyani (MDS) <sup>\*2</sup>, P. Dhanalakshmi <sup>#3</sup>  
<sup>#1</sup> Engineering Wing, Annamalai University, Annamalainagar, Tamilnadu, India.  
<sup>\*2</sup> Dept of Oral Pathology and Microbiology, RMDCH, Annamalai University, Annamalainagar, Tamilnadu, India.  
<sup>#3</sup> Associate Professor, Department of CSE, Annamalai University, Annamalainagar, Tamilnadu, India.

## Abstract

Leukoplakia is the most common potentially malignant disorder of the oral mucosa. Usually it is diagnosed by the exclusion of other lesions, which present as oral white plaques like lichen planus, chronic cheek bite, frictional keratosis, tobacco - induced keratosis, leukoedema and white sponge nevus. In this paper the leukoplakia microscopic images are taken and the feature extraction has been achieved using Block Intensity code comparison. After the feature extraction has been done the Radial Basis Function Neural Network classifiers the leukoplakia images from normal to abnormal. The performance has been achieved.

**Keywords** - Radial Basis Function Neural Network (RBFNN), Block Intensity Code Comparison (BICC), Oral leukoplakia, Erythroleukoplakia, Preleukoplakia.

## I. INTRODUCTION

Oral leukoplakia more commonly occurs in those who smoke but often the cause is unknown hence the name idiopathic leukoplakia. Chewing tobacco is also associated with this type of lesion. Leukoplakia is a premalignant lesion. In other words, leukoplakia denotes a negative diagnosis obtained histologically. It represents an area localized in distribution, hyperkeratosis in nature, and white in appearance due to wetting of the keratotic patch while in contact with saliva. It should be stressed that the diagnosis of leukoplakia denotes mainly, in two ways the first is that the mucosa is irritated by either mechanical, chemical or galvanic means and the next is that the mucosa is trying to adapt to the noxious stimuli by undergoing hyperkeratinisation of its surface. Since leukoplakia is an adaptive response, offered by a viable and healthy oral mucosa against some forms of sustained, low-grade irritant, it is irrational to consider it as a disease entity (hence its assumption of a negative diagnostic state) [1],[11].

Oral leukoplakia has recently been redefined as "a predominantly white lesion of the oral mucosa

that cannot be characterized as any other definable lesion; some oral leukoplakia will transform into cancer". A definitive diagnosis is made when it is histopathologically examined. The term preleukoplakia is sometimes used when the whiteness is not very distinct and should not be confused with leukoedema hereditary malformation of the oral mucosa [11].

Clinical manifestations of oral leukoplakia can take different forms defined according to the clinical pattern (homogenous or nonhomogenous), distribution or spread of the lesion (focal or disseminated), and location within the oral cavity. The homogenous pattern refers to lesions with a regular, smooth whitish surface and well (5%). The non homogenous pattern includes leukoplakias that are associated with an erythematous component (erythroleukoplakia) or a nodular, erosive, ulcerated or verrucous exophytic component. Malignization occurs in 25% of cases and so it is considered high-risk. Proliferative verrucous leukoplakia, currently considered as an independent entity from the set of leukoplakias is associated with a high risk of malignization; as many as 80% may become malignant[7]. Figure 1: shows the block diagram of Leukoplakia classification System.

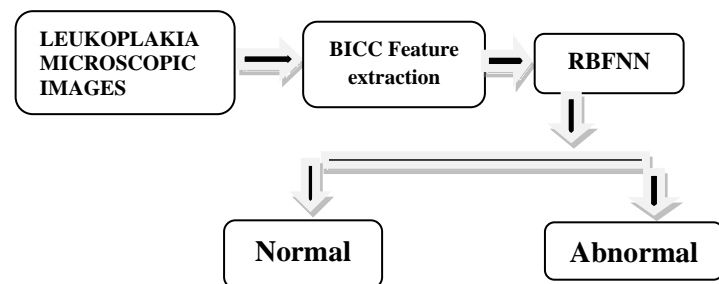


Fig 1: Block Diagram of Leukoplakia Classification System

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**Fig 2: Homogenous Leukoplakia**



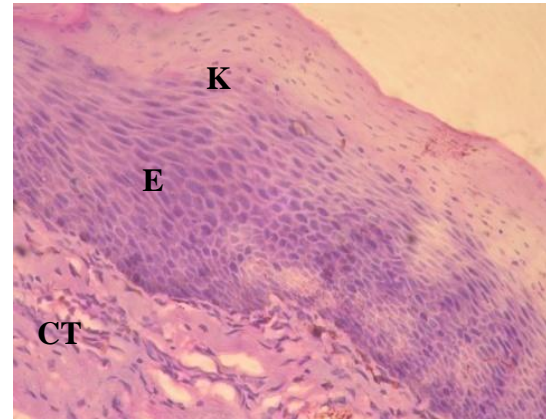
**Fig 3: Heterogenous Leukoplakia**

**Fig 2 and Fig 3 Show Sample Images of Patients having homogenous and heterogeneous leukoplakia respectively.**

Leukoplakia located on the floor of the mouth and in the ventrolateral region of the tongue are associated with a greater risk of malignization, with an average rate of transformation of 43%. This is attributed to the fact that these areas are more exposed to carcinogens in salivary secretions and that the epithelium is more permeable in this area, as indicated by experimental studies of oral mucosa

Leukoplakia is a clinical term and its use carries no implications with regard to the histological findings. However, it is recommended that a histological report should always include a statement

on the presence or absence of epithelial dysplasia and if present, the assessment of its severity. Epithelial dysplasia, if present, may range from mild to severe. In some instances, carcinoma in situ and even squamous cell carcinoma are encountered histologically [1]. Moderate hyperkeratosis and epithelial hyperplasia without dysplasia are the most common histological findings reported for leukoplakia .



**Fig 4: Microscopic Image of Leukoplakia**

**Fig 4:** shows the microscopic image of leukoplakia. The epithelium is hyperplastic. Also the hyperkeratinisation is seen on the superficial aspect.

On the basis of the lowest reported annual malignant transformation rate of oral leukoplakia, it can be calculated that patients with oral leukoplakia carry a 5 fold higher risk of developing oral cancer than controls. Leukoplakia occurs more frequently in smokers of tobacco than in non-smokers. There is a dose-response relationship between tobacco usage and the prevalence of oral leukoplakia. In addition to tobacco use, intake of specific nutrients and their deficiency may have a role in the development and progression of oral precancerous lesions [6].

Infections by Candida, Human PapillomaVirus and more recently, Epstein Barr Virus have been identified as cofactors that may affect the prognosis of established leukoplakia [3].

**Fig 5: shows the picture of oral cancer arising from leukoplakia.**



Fig 5: Oral Cancer arising from Leukoplakia; OC-Oral Cancer, L-Leukoplakia

## II FEATURE EXTRACTION

### A. BICC Feature Extraction

BICC features characterize the intensity variations between blocks in an image. The intensity changes between blocks of a frame are represented by block intensity comparison code [9]. To extract the BICC features, each image is divided into blocks of size  $K \times K$ . Images of size  $326 \times 244$  are used for experimental studies. BICC is computed as follows:

1. Divide the frame into  $5 \times 5$  blocks. (Fig. 5.5)
2. Compute the average intensity in each block.
3. Compare the average intensity values of each block in an image with every block in the image.
4. BICC is generated using the formula (1):

$$Y \left[ (i-1) 25 + j - \frac{i(i+1)}{2} \right] = \begin{cases} 1 & \text{if } x(i) > x(j) \\ 0 & \text{otherwise,} \end{cases}$$

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

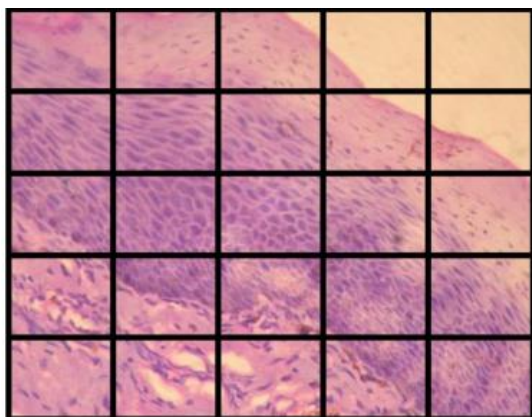


Fig 6: Leukoplakia image divided into blocks of size  $5 \times 5$

### B. Radial Basis Function Neural Network (RBFNN)

Radial Basis Function Neural Network (RBFNN) is a type of Artificial Neural Network (ANN). It has feedforward architecture with an input layer, a hidden layer, and an output layer. It is applied to the problems of supervised learning and associated with radial basis functions. RBFNN trains faster than multi-layer perceptron[7]. It can be applied to the fields such as control engineering, time-series prediction, electronic device parameter modeling, speech recognition, image restoration, motion estimation, data fusion, etc.

### C. Architecture of Radial Basis Function Neural Network

Radial Basis Functional Neural Networks (RBFNN) provide an outstanding possibility for generating rules for solving pattern classification problems. The architecture of RBFNN is shown in Fig. 3.2. Radial basis functions are embedded into a two-layer feed forward neural network. Such a network is characterized by a set of inputs and a set of outputs. In between the inputs and outputs there is a layer of processing units called hidden units. Each of them implements a radial basis function. The input layer of this network has  $n_i$  units for a  $n_i$  dimensional input vector. The input units are fully connected to the  $n_h$  hidden layer units, which are in turn fully connected to the  $n_c$  output layer units, where  $n_c$  is the number of output classes.

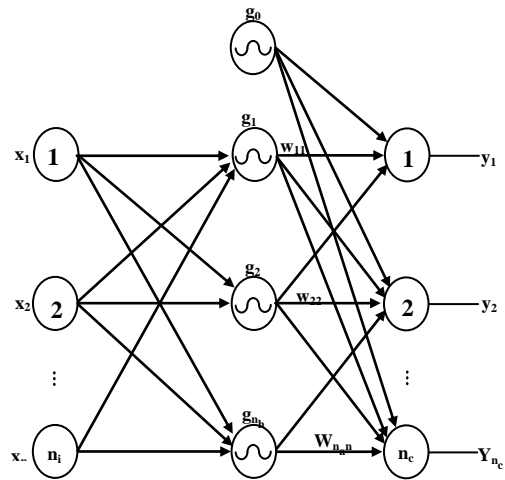


Fig. 7: Architecture of Radial Basis Function Neural Network

The activation functions of the hidden layer were chosen to be Gaussians and are characterized by their mean vectors (centers)  $\mu_i$ , and covariance matrices  $C_i$ ,  $i = 1, 2, \dots, n_h$ . For simplicity, it is assumed that the covariance matrices are of the form  $C_i = \sigma_i^2 I$ ,  $i = 1, 2, \dots, n_h$ . Then the activation function of the  $i^{\text{th}}$  hidden unit for an input vector  $x_j$  is given by

$$g_i(x_j) = \exp\left(\frac{-\|x_j - \mu_i\|^2}{2\sigma_i^2}\right)$$

**III. PERFORMANCE MEASURES**

Sensitivity and Specificity are statistical measures used for studying the performance of classification. Sensitivity measures the proportion of actual positives which are correctly identified

$$sensitivity = \frac{True\ positive}{(True\ positive + False\ negative)} \quad (2)$$

**IV. EXPERIMENTAL RESULTS**

**A. Database**

Normal and Leukoplakia affected tissue images were collected from patients of Raja Muthiah Dental College and Hospital (RMDC & H). The dataset of 200 Microscopic images was collected 100 were of normal microscopic images and 100 were of affected images which was classified by RBFNN classifier.

A total of 200 microscopic images which consists of 100 leukoplakia images and 100 normal images are considered.

**Table 1: Shows the Sensitivity and Specificity for Leukoplakia Microscopic Images.**

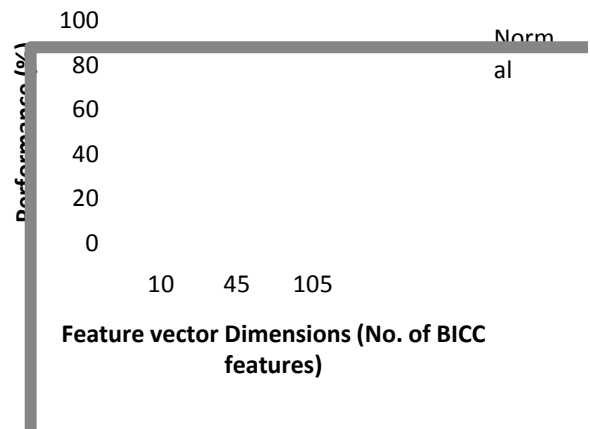
Performance Measures	Accuracy (%)
Sensitivity	74 %
Specificity	88 %

For RBFNN training, BICC features are extracted from the images for each category. These features are given as input to the RBFNN model. In Radial Basis Function Neural Network, the weights in the network are determined using the least squares algorithms. For training BICC features for blocks of size 5 x 5, 10 x 10 and 15 x 15, resulting in 16, 45 and 105 dimensional feature vectors respectively which are extracted from the images. These features are given as input to the RBFNN model. The RBF centers are located using k-means algorithm. For each category the value of k is varied from 2 to 8. The system gives optimal performance for k = 6. The weights in the RBFNN network are determined using the least square algorithm. For testing, if the output of the network is greater than the threshold, then it represents a leukoplakia affected image. k-means algorithm. For each category the value of k is varied from 2 to 8. The system gives optimal performance for k = 6. The weights in the RBFNN network are determined using the least square algorithm. For testing, if the output of the network is greater than the threshold, then it represents a leukoplakia affected image.

Fig 7: shows the performance of classifying Leukoplakia by RBFNN and the model gives a better performance with k = 6

**Table 2: Average Performance of Normal and Leukoplakia Classification by RBFNN Model Using BICC Features**

No. of means	Accuracy( % )					
	Feature vector dimensions (No. of BICC features)					
	10		45		105	
	Normal	Leukoplakia	Normal	Leukoplakia	Normal	Leukoplakia
2	88.0	89.0	87.0	89.2	88.7	90.4
4	86.0	89.5	88.6	90.5	89.0	91.6
6	90.0	91.0	89.4	92.0	94.5	96.0
8	89.0	90.3	89.1	91.9	92.4	94.5



**Fig 7 :Average performance of normal and Leukoplakia Classification by RBFNN Model with k = 6 using BICC Features**

**V. CONCLUSION**

The performance of Leukoplakia using RBFNN has been analyzed. BICC features are extracted to characterize the leukoplakia images. The above-mentioned classifiers are applied to obtain the optimal class boundary between the two classes namely leukoplakia and normal images by learning from training data. The classification rate using 105 BICC features showed an accuracy of above 90.0% in the models. RBFNN shows the highest accuracy of 96% for leukoplakia classification, for 105 BICC features.

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