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SVM BASED CLASSIFICATION OF EPITHELIAL DYSPLASIA USING SURF AND SIFT FEATURES

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Abstract

Leukoplakia is a potentially malignant disorder that could occur in the oral cavity which presents as a white or grayish keratotic patch. Leukoplakia in general is a clinical terminology and term should be replaced as 'Epithelial dysplasia' by the diagnosis obtained histopathologically .The destructive change rate of leukoplakia to oral squamous cell carcinoma was seen to be 3.5% with a wide range in the region of 0.13% and 34.0% and may move in different parts of the world, in perspective of the probability of tobacco usage and dietary penchants. Clinical analysis of epithelial dysplasia prompts mistakes. There is no particular methodology or test to perceive the epithelial dysplasia. PC Aided Diagnosis (CAD) gives the exact outcomes to identify the epithelial dysplasia. These CAD can be embedded into constant applications for the early conclusion of the epithelial dysplasia .This paper endeavors to characterize the dysplastic epithelium by the Speeded Up Robust Feature extraction and Scale-invariant Feature Transform and it has been classified using SVM classifier, since epithelial dysplasia is a vital factor for expectation of harmful change.

Keywords: Oral cancer (OC), Speeded Up Robust Features(SURF), Scale-invariant Feature Transform(SIFT), Support Vector Machine (SVM).

1. Introduction:

Oral mucosa- a mirror that reflects an individual's health, which lines the oral cavity usually, consists of surface epithelium, basement membrane and underlying connective tissue. The oral epithelium includes aggregated keratinocytes (Cells produces Keratin) fused by

desmosomes and it is arranged in various layer such as stratum corneum, stratum granulosum, stratum spinosum and stratum basale.

In general oral mucosa is subjected to various diseases states and condition due to many etiological factors like Physical, Chemical & Thermal injuries, Autoimmunity and Immunologically mediated diseases, micro-organism, Psychological, Idiopathic and other systemic condition etc[2]. The principle function of epithelium is to protect from these various environmental insult by its integrity, keratin production, selective absorption and sensing etc.

Leukoplakia (Leuko-White and Plakia-a plate or a level plane) is the most well-known white lesion of the oral depression like in vermilion fringe, buccal mucosa, gingival mouth, lip, tongue, floor, sense of taste and so on. There are distinctive etiologies of leukoplakia which consolidates tobacco, alcohol, sanguinaria, splendid radiation, damage and microorganism like treponema palladium, candida albicans and papilloma disease. This injury is for the most part found in individuals under forty years of age and predominant in Men.

World Health Organization ordered 'Leukoplakia' as a Potentially harmful turmoil and Oral malignancy is the 6th most powerless disease on the planet, which represents more than 30% of all growths announced in the nation and oral tumor control is rapidly turning into a worldwide wellbeing need. The threatening change rate of leukoplakia to oral squamous cell carcinoma was observed to be 3.5% with a wide range in the vicinity of 0.13% and 34.0% and fluctuates in various parts of the world, in view of the likelihood of tobacco utilization. Figure 1: shows the normal Microscopic image.

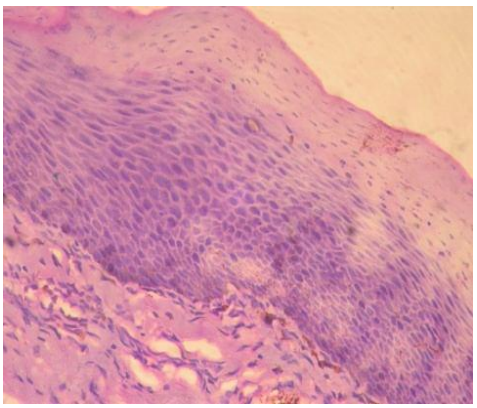

Figure 1: Normal Microscopic image

Leukoplakia in general is a clinical terminology and term should be replaced as ‘Epithelial dysplasia’ by the diagnosis obtained histopathologically. As[9] the basic histological highlights of epithelial dysplasia incorporates the loss of extremity of the basal cells, basillar hyperplasia, increased atomic cytoplasmic proportion .

1.2. OUTLINE OF THE WORK

In this work, photomicrograph images of oral mucosa were taken. The objective of this work is to separate ordinary and epithelial Dysplasia images using two novel feature extraction techniques SURF and SIFT. The RGB images are converted into HSV color space . Support vector machine (SVM) is trained and tested to obtain the optimal class boundary . The experimental results show that the classification accuracy of SVM with SURF Features.

The paper is organized as follows. The Color Space is described in Section 2. The feature extraction is presented in Section 3, modeling techniques for image classification is described in Section 4. Experimental results using SVM are reported in Section 5. Finally, Results and discussion are given in Section 6.

2. COLOR SPACE

A color space is defined as a model for representing color in terms of intensity values with one-to four-dimensional space. A color component, or a color channel, is one of the dimensions. In this proposed work, HSV color space is used.

2.1. A. HSV Color Space

HSV stands for hue, saturation, and value. The value represents intensity of a color, which is decoupled from the color information in the represented image. The hue and saturation components are intimately related to the way human eye perceives color resulting in image processing algorithms with physiological basis.[9] As hue varies from 0 to 1.0, the corresponding colors vary from red, through yellow, green, cyan, blue, and magenta, back to red, so that there are actually red values both at 0 and 1.0. As saturation varies from 0 to 1.0, the corresponding colors (hues) vary from unsaturated (shades of gray) to fully saturated (no white component). As value, or brightness, varies from 0 to 1.0, the corresponding colors become increasingly brighter.

2.1. B. Color Conversion

In order to use a good color space, color conversion is needed between color spaces which preserve the perceived color differences.

2.1. C. RGB to HSV Conversion

Initially, the *R, G, B* values are divided by 255 to change the range from 0...255 to 0...1:

$$R' = R/255$$

$$G' = G/255$$

$$B' = B/255$$

$$C_{\min} = \min(R', G', B')$$

$$\Delta = C_{\max} - C_{\min}$$

In this work the RGB photomicrography images are taken and it is converted into the HSV conversion. And the value image (intensity) are taken for processing.

3. Feature Extraction

3.1. Surf Feature Extraction

The SURF algorithm is based on the same principles and steps as SIFT; but details in each step are different. The algorithm has three main parts: interest point detection, local neighborhood description and matching.

3. 1. A. Detection

SURF uses square-shaped filters as an approximation of Gaussian smoothing. Filtering the image with a square is much faster if the integral image is used:

$$S(x, y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i, j) \tag{1}$$

The determinant the Hessian matrix is used as a measure of local change around the point and points are chosen where this determinant is maximal. SURF also uses the determinant of the Hessian for selecting the scale, as is also done by Lindeberg. Given a point p=(x, y) in an image I, the Hessian matrix H(p, σ) at point p and scale σ, is:

$$H(p, \sigma) = \begin{pmatrix} L_{xx}(p, \sigma) & L_{xy}(p, \sigma) \\ L_{yx}(p, \sigma) & L_{yy}(p, \sigma) \end{pmatrix} \tag{2}$$

where $L_{xx}(p, \sigma)$ etc. is the convolution of the second-order derivative of gaussian with the image $I(x, y)$ at the point x.The box filter of size 9×9 is an approximation of a Gaussian with σ=1.2 and represents the lowest level (highest spatial resolution) for blob-response maps.

3.1. B. Scale-space representation and location of points of interest

Interest points can be found at different scales, partly because the search for correspondences often requires comparison images where they are seen at different scales. In other feature

detection algorithms, the scale space is usually realized as an image pyramid. [6] Images are repeatedly smoothed with a Gaussian filter, then they are sub sampled to get the next higher level of the pyramid. Therefore, several floors or stairs with various measures of the masks are calculated:

$$\sigma_{approx} = \text{current filter size} \times \left(\frac{basefilterscale}{basefiltersize} \right) \tag{3}$$

The scale space is divided into a number of octaves, where an octave refers to a series of response maps of covering a doubling of scale. In SURF, the lowest level of the scale space is obtained from the output of the 9×9 filters.

Hence, unlike previous methods, scale spaces in SURF are implemented by applying box filters of different sizes. Accordingly, the scale space is analyzed by up-scaling the filter size rather than iteratively reducing the image size

3.1. C. Descriptor

The goal of a descriptor is to provide a unique and robust description of an image feature, e.g., by describing the intensity distribution of the pixels within the neighbourhood of the point of interest. Most descriptors are thus computed in a local manner, hence a description is obtained for every point of interest identified previously. The first step consists of fixing a reproducible orientation based on information from a circular region around the interest point. Then we construct a square region aligned to the selected orientation, and extract the SURF descriptor from it.

3.1. D. Orientation assignment

In order to achieve rotational invariance, the orientation of the point of interest needs to be found [4].The Haar wavelet responses in both x- and y-directions within a circular neighbourhood of radius $6s$ around the point of interest are computed, where s is the scale at which the point of interest was detected

3.1.E. Matching

By comparing the descriptors obtained from different images, matching pairs can be found.

3.2. SIFT FEATURE EXTRACTION

SIFT (Scale Invariant Feature Transform) algorithm proposed by Lowe in 2004 [6] to solve the image rotation, scaling, and affine deformation, viewpoint change, noise, illumination changes, also has strong robustness. The SIFT algorithm has four main steps: (1) Scale Space Extrema Detection, (2) Key point Localization, (3) Orientation Assignment and (4) Description Generation. The first stage is to identify location and scales of key points using scale space

extrema in the DoG (Difference-of-Gaussian) functions with different values of σ, the DoG function is convolved of image in scale space separated by a constant factor k as in the following equation

$$D(x, y,\sigma) = (G(x, y, k\sigma) - G(x, y,\sigma) \times I(x, y) \quad (5)$$

Where, G is the Gaussian function and I is the image.Now the Gaussian images are subtracted to produce a DoG, after that the Gaussian image subsample by factor 2 and produce DoG for sampled image. A pixel compared of 3×3 neighborhood to detect the local maxima and minima of D(x, y, σ).

In the key point localization step, key point candidates are localized and refined by eliminating the key points where they rejected the low contrast points. In the orientation assignment step, the orientation of key point is obtained based on local image gradient. In description generation stage is to compute the local image descriptor for each key point based on image gradient magnitude and orientation at each image sample point in a region centered at key point [2]; these samples building 3D histogram of gradient location and orientation; with 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor.

3.2. A. Construction Of SIFT Descriptor

Figure 1 illustrates the computation of the key point descriptor. First the image gradient magnitudes and orientations are sampled around the key point location, using the scale of the key point to select the level of Gaussian blur for the image [6]. In order to achieve orientation invariance, the coordinates of the descriptor, then the gradient orientations are rotated relative to the key point orientation. Figure 2: illustrated with small arrows at each sample location on the left side.

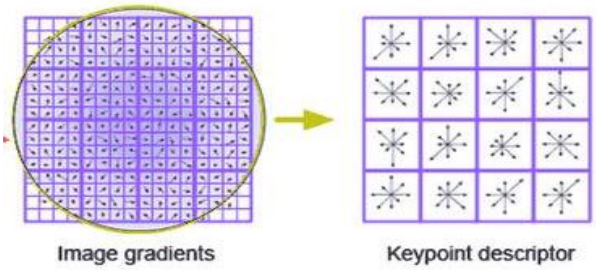

Figure 3.2.A: Key point descriptor

The key point descriptor is shown on the right side of Figure 3.2.A. It allows for significant shift in gradient positions by creating orientation histograms over 4x4 sample regions. The figure

shows 8 directions for each orientation histogram [6], with the length of each arrow corresponding to the magnitude of that histogram entry. A gradient sample on the left can shift up to 4 sample positions while still contributing to the same histogram on the right. So, 4×4 array location grid and 8 orientation bins in each sample. That is 128-element dimension of key point descriptor.

4. Modeling techniques for image classification

4.1 SUPPORT VECTOR MACHINES (SVM)

SVM is a statistic machine learning technique that has been successfully applied in the pattern recognition area and, is based on the principle of structural risk minimization. SVM builds a straight model to assess the choice capacity utilizing non-direct class limits in light of help vectors. [2] SVM learns an optimal separating hyper plane from a given set of positive and negative Figure 1: shows the architecture of the SVM. It maps the input patterns into a higher dimensional feature space through some nonlinear mapping chosen a priori. A linear decision surface is then constructed in this high dimensional feature space. Thus, SVM is a linear classifier in the parameter space, but it becomes a non-linear classifier as a result of the nonlinear mapping of the space of the input patterns into the high dimensional feature space.

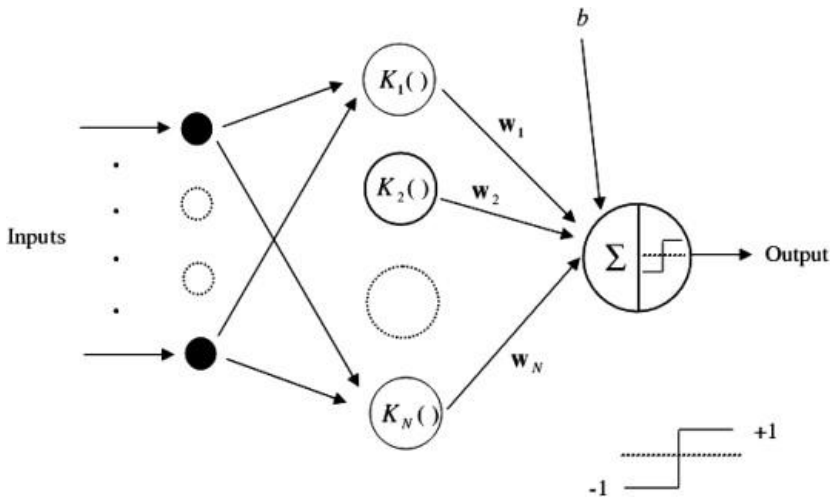

Figure 4.1: Architecture of the SVM (Ns is the number of support vectors).

The kernel function may be any of the symmetric functions that satisfy the Mercer's conditions. There are several SVM kernel functions as given in table 1.

Table 1 : Types of SVM inner product kernel

Types of Kernals	Inner product Kernal $k(x^T, x_i)$	Details
Polynomial	$(x^T x_i + 1)^P$	Where x is the input streams x_i is the support vector
Gaussian	$\exp\left[-\frac{\left\|x^T - x_i\right\|^2}{2\sigma^2}\right]$	σ^2 is a variance, $1 \le i \le N_s$, N_s is the number of support vectors,
Sigmoidal	Tanh ($\beta_0 (x^T x_i) + \beta_1$)	β_0, β_1 are constant values P is degree of the polynomial.

5. EXPERIMENTAL RESULTS

5. 1. Dataset

Normal and epithedial dysplasia affected tissue images were collected from patients of Raja Muthiah Dental College and Hospital (RMDC & H).The dataset of 180 Microscopic images was collected: 75 normal microscopic images and 100 epithedial dysplasic images. The classification was made by SVM classifier. A total of 175 microscopic images which consists of 75 normal images and 100 images shows the abnormalities.

The implementation of the proposed system was shown in Figure 5,6.The Figure 5 shows the RGB to HSV converted image. By selecting the HSV conversion image the image has be

converted into Hue, Saturation and Value (Intensity) image. In which Value(Intensity) image is taken for manipulation.

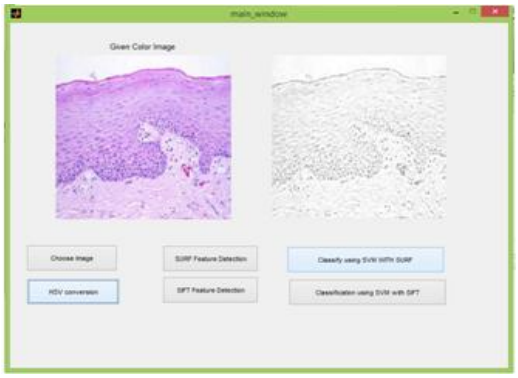

Figure 5: Conversion of RGB to HSV

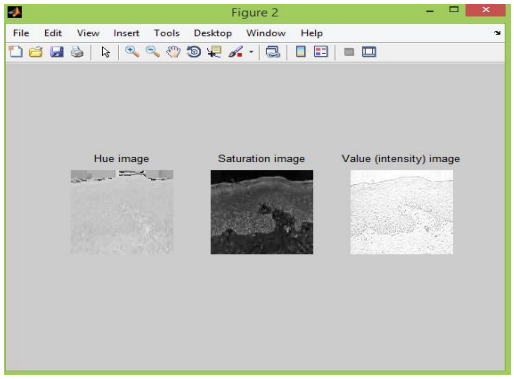

Figure 6: HSV converted image which shows the Hue, Saturation and Value images

5.2. RECOGNITION OF DISEASE WITH SURF USING SVM

In the proposed work SURF points are detected and they are extracted and given to the SVM classifier .Figure 5.2.A: shows the points that has been found. In the below figure 64 key points have been detected. Figure 5.2.B : shows the performance accuracy 92.15%

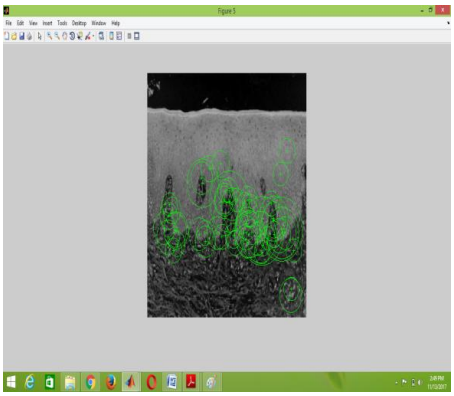

Figure 5.2.A: The Feature detection measures of using SURF

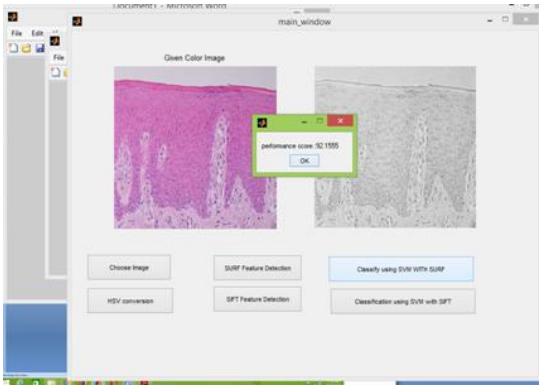

Figure5.2.B: Shows the performance SURF using SVM

5.3. RECOGNITION OF DISEASE WITH SIFT USING SVM

In the proposed work SIFT points are detected and they are extracted and given to the SVM classifier. Figure 5.3.A : shows the points that has been found. In the below figure key points have been detected. Figure 5.3.B

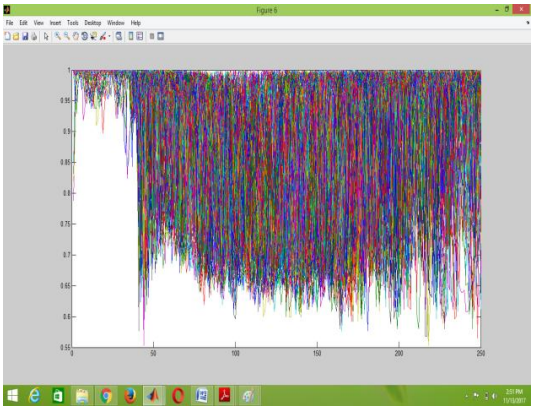

Figure 5.3.A: The feature detection using SIFT

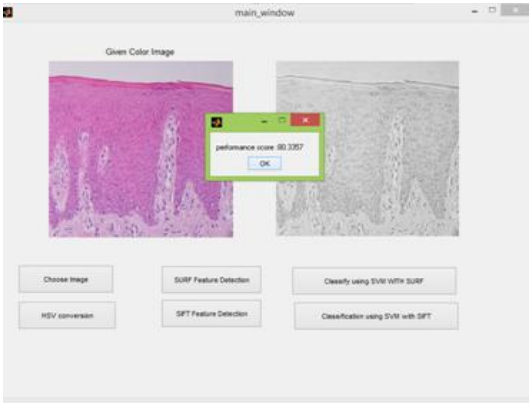

Figure 5.3.B: Shows the performance measures of SIFT using SVM

6. Results and Discussion

The below Figure 6 shows the comparison of surf and sift performance. Few samples were taken in order to make the overall comparison. When compared with both the features surf shows the overall highest performance of 95.25% than the sift whose overall performance is 84.18%

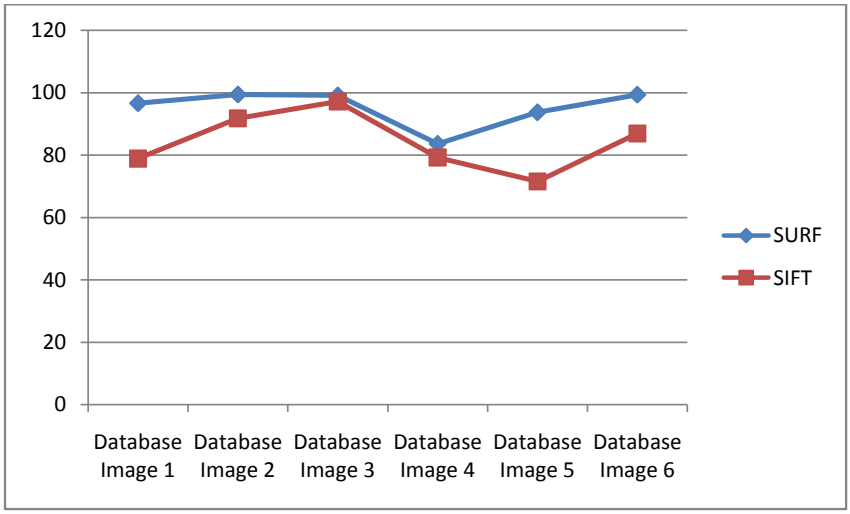

Figure 6 :Performance comparison of SURF and SIFT

Conclusion

In this work, the images are captured and the series of operations are performed to identify the classification as normal or epithelial dysplasia. The RGB images are converted into HSV Color space and features are extracted using SURF, SIFT . Further SVM classifier is used for classification. Accuracy obtained for SURF feature extraction is 91.4% . SURF gives a better performance when compared with SIFT in SVM technique

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