RESEARCH ARTICLE OPEN ACCESS

A Novel Method for Automatic Detection of Early Stage Oral Cavity Cancer

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ABSTRACT
Oral cavity cancer, or oral cancer, is a malignant tumor that starts in mouth. It is one of the most widely recognized of all cancer which affects human beings. Oral cancer can be averted by staying away from tobacco items, constraining liquor use, sun protection on the lower lip, HPV immunization, and evasion of paan. Oral malignancy can be relieved at high rates with basic and practical medications, whenever distinguished at its earlier stages. At earlier stages, Oral cancer can be automatically diagnosed. The basic aim of this "A Novel Method for Automatic Detection of Early Stage Oral Cancer" is a simple, efficient and automatic oral cancer detection system with the utilization of available software for non-specialists/clinicians/specialists. In this approach, Pre-processing of image is performed by utilizing anisotropic diffusion filter for removing the noise and enhancing the image quality. Fuzzy C-Means (FCM) is used for image segmentation. Gray Level Co-Occurrence Matrix (GLCM) is utilized for textural feature extraction. Extracted textural features are energy, homogeneity, contrast, correlation. Support Vector Machine (SVM) is used to classify whether oral malignancy tumour detected or not. Finally the proposed system performance will be evaluated by calculating the parameters such as accuracy, specificity and sensitivity.
Keywords - Anisotropic Diffusion, Fuzzy C-Mean (FCM), Image Pre-processing, Image segmentation, SVM (Support Vector Machine), Tumor classification**.**

Date Of Submission: 22-06-2019 Date Of Acceptance: 08-07-2019

I. INTRODUCTION

Oral cavity cancer, otherwise called mouth disease, is a complex disease arising in various organs including tongue, lining of the lips, mouth, gum, upper throat and the floor of the mouth. In the mouth, it most ordinarily begins as a determined white fix, which thickens, creates red fixes, a ulcer, and keeps on developing. On the lips, it normally resembles a constant crusting ulcer that does not recuperate, and gradually develops. Different indications may incorporate troublesome or excruciating gulping, new protuberances or bumps in the neck, a swelling in the mouth, or a feeling of numbness in the mouth or lips. With both tobacco and drinking alcohol the risk of oral cancer is 15 times greater. Other risk factors include HPV infection, chewing paan, and sun exposure on the lower lip. Oral cancer is a subgroup of head and neck cancers. Diagnosis is made by biopsy of the concerning area, followed by investigation with CT scan, MRI, PET, and examination to determine if it has spread to distant parts of the body. Oral cancer can be prevented by avoiding tobacco products, limiting alcohol use, sun protection on the lower lip, HPV vaccination, and avoidance of paan.

Medicines utilized for oral malignant growth can incorporate a mix of medical procedure (to evacuate the tumor and provincial lymph hubs), radiation treatment, chemotherapy or focused on treatment. The kinds of medicines will rely upon the size, areas, and spread of the malignancy taken into consideration with the general health of the person. Somewhere in the range of 1999 and 2015 in the United States rate of oral malignant growth expanded 6% (from 10.9 to 11.6 per 100,000).

Despite the fact that smoking abandonment campaigns have decreased the rate of tobacco, the rate of HPV related malignancies has counterbalanced the additions. Demise from oral malignancy deceased 7% (from 2.7 to 2.5 per 100,000). Oral disease has a general survival rate of 63%but shifts broadly relying upon when treatment is begun. Whenever treated early, oral malignant growth has a 84% 5-year survival rate, contrasted with 65% in the event that it has spread to the lymph nodes in the neck, and 39% in the event that it has spread far from the parts of the body.

Survival rates likewise are exceptionally reliant on the area of the sickness in the mouth. Tumors are either benign or malignant. Malignant tumors are carcinogenic. Precancers and early time oral malignant growths can't be sufficiently distinguished by visual assessment alone and might be ignored and disregarded.

Orthopantomograms are the Dental Panoramic Radiographs which recognize issues with teeth, mouth and jaw. Dental radiographs are utilized for screening oral pathologies consistently and it is frequently a troublesome task to discover early stage cancer in a dental radiograph. Thus, Image Processing procedures have been effectively applied on dental radiographic pictures to select helpful data for biomedical applications.

II. RELATED WORK

Abdolali, Zoroofi et al. [1], discussed about the automatic segmentation algorithm dependent on the symmetric axis investigation, which is an examination of the left and right sides of each picture. The point was to find the distinction in intensity where the tumor exists. This examination accomplished high positive outcomes including different sorts of cysts. Nevertheless, the detection failure will occur if the tumor is in the middle or on either side of the image. The pre-processing technique, an anisotropic pre-processing, utilized in this investigation diminished the disturbance on the CT picture in the interim further improve the quality of edge area in the oral depression.

Alsmadi [2] proposed a hybrid method by consolidating Fussy C-Means and "neutrosophic" calculation for segmentation of tumors in the oral panoramic picture proposed . It used speckle reduction by 3 × 3 size median filter to reduce the speckle noise, then reducing image noise with the neutrosophy algorithm. This approach provided a significant improvement in segmenting oral lesions. The accuracy comes from the use of indeterminacy degree to cluster the region and determination of the tumor. In any case, as this examination depends on cluster calculation and image boundary location, shadow regions on the panoramic picture will be a concern as far as false discovery. An investigation used variations of SVM, for example, Linear SVM, Quadratic SVM and Cubic SVM, to characterize tumors on optical coherence tomography images.

Banerjee et al. [3], estimated the sensitivity, specificity and accuracy in 6 diverse grouping conditions. They found the highest solution. This research is based on biopsy images, and the accuracy is coming from the high quality of the images. Thus, it is clear that low-quality or noisy images would be a concern.

Chang et al. [4], proposed and tested five tumor classification methods. The method, ANFIS, achieved the highest classification rate by combining the clinic pathologic dataset and biopsy images. This study considers patient's case as a whole. However, if the clinic pathologic dataset or images are considered in isolation, this solution will not achieve over highest accuracy rate. In other words, the accuracy of this method is relying on the patient's information.

Warnakulasuriya [5] evaluated that, malignancy is the real reason for morbidity and mortality everywhere throughout the world and is one of the main sources of death in all social orders, with its relative position differing with age and sex.Oral SCC more oftentimes influences men than ladies (M: F= 1.5:1) most likely on the grounds that a bigger number of men than ladies indulge in high-risk habits.The possibility of developing oral SCC increments with the time of disclosure to risk factors, and increasing age includes the further component of age-related mutagenic and epigenetic changes. In the USA the middle period of analysis of oral SCC is 62 years. The frequency of oral SCC in people younger than 45 is expanding. The cause behind this is uncertain.

Elango et al. [6], discussed that oral disease is any threatening neoplasm which is found on the lip, floor of the mouth, roof of the mouth or in the tongue. Oral malignant growth is among the main three kinds of tumors in India.

Lin et al. [7], examined that extreme liquor misuse, utilization of tobacco like cigarettes, smokeless tobacco, betel nut biting and contamination with human papilloma infection (HPV) are the most widely recognized hazard factors for oral malignancy. Oral malignant growth may likewise happen because of poor dental consideration and bad routine.

Bray et al. [8], investigated that the worldwide agency for research on disease has anticipated that India's occurrence of malignant growth will increment from 6, 80,000 to 1-2 cardinal in a similar period. No critical improvement in the treatment of oral malignant growth has been found lately, however the present treatment improve the nature of life of oral disease patients yet the general survival rate of 5 years has not improved in the previous decades.

Gillenwater et al. [9], researched that oral squamous cell carcinoma (OSCC) is the 6th most normal danger and is a serious reason for malignancy and mortality around the world. The general survival rate has not changed as of late, in spite of broad research on the natural and sub-atomic parts of oral squamous cell carcinoma. Among the all the more squeezing issues in clinical administration are the absence of early recognition and the high rate of nearby local intermittent, even with careful treatment.

Bagan et al. [10], suggested that various conditions have been related with a raised danger of creating oral SCC including Li Frau-meni disorder, Plummer-Vinson disorder, Fanconi iron deficiency, chemotherapy instigated immunosuppression of organ transplantation, dyskeratosis congenita, xeroderma pigmentosum and discoid lupus erythematosus . In Western nations oral SCC infect the tongue in 20% - 40% of cases and the floor of the mouth in 15% - 20% of the cases, and together these area represent about half of all instances of oral SCC . The gingivae, palate, retromolar region and the buccal and labial mucosa are oral area less regularly influenced.

Neville B and Day [11], recommended that the inward surface of the tongue and the floor of the mouth are the most frequently damaged since they are lined by slender non-keratinised epithelium. Not exclusively do cancer-causing agents promptly enter this slender epithelium to achieve the begetter cell compartment; however cancer-causing agents, especially tobacco items and liquor in arrangement, continually collect in the floor of the mouth and wash the tissues of the floor of the mouth and the ventrum of tongue.

Scully and Bagan [12], suggested that Oral SCC may take varoius clinical structures. It might look like a leukoplakia, a verrocous leukoplakia, an erythroleukoplakia, or an erythroplakia, any of which may in the long run form into a necrotic looking ulcer with unpredictable, raised indurated outskirts or into an expansive based exophytic mass with a surface which might be verrucous, pebbled or moderately smooth.

Slaughter et al. [13,14] , recommended that "Field cancerization" alludes to the potential improvement of malignancy at different sites.This has been seen during the advancement of disease in the tissues shielded with squamous epithelium (head and neck tumor) and transitional epithelium (urothelial carcinoma). It is obvious that oral malignant growth, similar to carcinomas in different tissues, establish over numerous years, and during this period, there are various areas of neoplastic change happening all through the oral cavity. "Field cancerization" may likewise be characterized by the outflow of transformations in the exons of tumor suppressor gene.

Day, Blot et al. [15], recommended that, Biomarkers help in assessing the preventative measures or treatments and the identification of the earliest phases of oral mucosal dangerous change. Biomarkers unveil the hereditary and sub-atomic changes related to early, intermediate, and late end-points in the process of oral carcinogenesis. These biomarkers will refine the capacity to improve the prediction, detection, and medication of oral Carcinomas.

McKeown-Eyssen et al. [16,17], proposed that , recommended that , Genetic and sub-atomic biomarkers will likewise decide the adequacy and security of chemopreventive operators.

Chemopreventive specialists are synthetic concoctions of common or manufactured cause. In contrast to different medications, which don't halt infection, chemopreventive operators lessen the frequency of sicknesses, for example, malignancy before clinical syndrome happen. This improvement is supreme for the early identification of oral mucosal change. Biomarkers will likewise decrease the quantity of patients and the ideal opportunity for long haul follow-up required to characterize a clinical reaction to a chemopreventive specialist. The markers may in this way explain the sorts, dosages, frequencies, and regimens to accomplish the greatest dimension of advantage from chemopreventive operators. Diminishing the expense of the clinical preliminaries is another factor that drives the advancement of biomarkers.

Shah and Gil [18], suggested that, the treatment of oral SCC normally requires the favour of a multidisciplinary group , the main point of treatment always being to eliminate the malignant growth, to avoid periodic, and to the extent that is to rehabilitate the structure and purpose of the influenced parts. The option of a particular treatment methodology is managed by the idea of the carcinoma and by the general state of the patient. Major aspect identified with the carcinoma incorporate the particular site influenced, the clinical size, the degree of nearby attack, histopathological characteristic, local lymph node association and inaccessible metastasis. Patient elements incorporate age, general health status, a past filled with recently treated oral SCC and high-threat practice.

III. PROPOSED MODEL

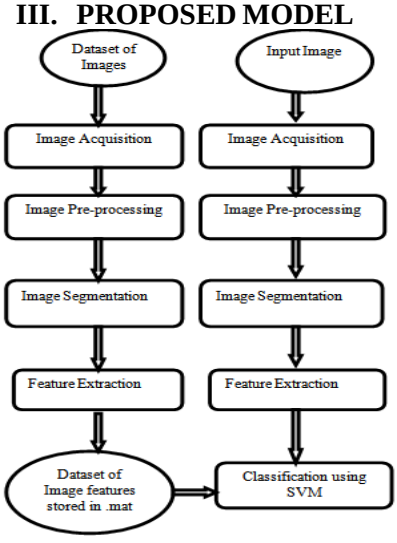


Fig 1. Proposed Model

1) Training – In training all the collected images are trained to the model and all features are extracted and stored.
2) Classification – After training, the SVM will classify the given new input as whether the oral cavity tumor is detected or not.

The proposed model in Fig.1 mainly consists of
1) Image collection
2) Image Pre-processing
3) Image segmentation
4) Feature extraction
5) Training
6) Classification using SVM

3.1. Image Collection

The sample pictures of the oral cavity (which comprises the lips, interlining of the lips and cheeks (buccal mucosa), the teeth, the gums, the floor of the mouth beneath the tongue, and the hard top of the mouth (hard palate)) are gathered and are utilized in training the system. To train and to test the system, sample images are taken. The images will be stored in some standard format.

3.2. Image Pre-processing

Image pre-processing is important for real information that are regularly noisy and uneven. During this phase, the transformation is applied to convert the image into another image to improve the quality that better suits for analyzing. This step constitute to a critical stage in image processing applications since the efficacy subsequent tasks (e.g., features extraction, segmentation) depends highly on images quality.

Anisotropic dissemination is utilized for both picture upgrade and denoising. The Perona-Malik model utilizes anisotropic dispersion to sift through the noise. In Perona-Malik model the rate of dispersal is obliged by edge stopping function.. The downside of Perona-Malik model is that the sharp edges and fine subtleties are not protected well in the denoised picture. In any case, the sharp edges and fine subtleties can be protected well utilizing suitable edge stopping function.

3.3. Image Segmentation

During image segmentation, the given image is separated into a homogeneous region based on certain features. Larger data sets are put together into clusters of smaller and similar data sets using clustering method. In this proposed work, fuzzy c means algorithm is used and the implementation is as follows.

3.3.1. Algorithm

In the proposed WIPFCM calculation, we supplant every pixel with its comparing picture patch and appoint a weight to every pixel in the picture patch. Accordingly, the objective function of our algorithm is as shown below (i.e. eq.1).

$$J_{WIPFCM} = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{m} \sum_{r\in N_k} \omega_{kr} \ \|I_{kr} - V_{ri}\|^2 \quad \ldots\ldots\ldots\ldots (1)$$

Where Vi = (vri, r ∈ N∗) is the q2 dimensional centroid of cluster i, U = {uik} ∈Rn×c is the membership matrix, m ∈ (1, ∞) is the fuzzy parameter, and||•|| 2 denotes the Euclidean distance operator.

Like the conventional FCM calculation, this objective function can be limited iteratively. The whole method of the proposed WIPFCM calculation can be encapsulated in the following steps:

Step 1. Empirical setting of parameters, including the width of image patch q, number of clusters c, fuzzy parameter m, error tolerance ε = 0.001, and max iterative steps Iter = 100;

Step 2. Get the image patch PIK for each pixel k;

Step 3. Initialize cluster centroids Vi, i = 1, . . ., c

Step 4. Compute the weight vector WIK for image patch PIK.

Step 5. Compute the membership function U as shown below (i.e. eq.2)

$$u_{ik} = \left\{ \sum_{j=1}^{c} \left[\left(\frac{\sum_{r\in N_k} \omega_{kr}(I_{kr} - v_{ri})^2}{\sum_{r\in N_k} \omega_{kr}(I_{kr} - v_{rj})^2} \right)^{1/(m-1)} \right] \right\}^{-1} \quad \ldots\ldots\ldots\ldots (2)$$

Step 6. Update group centroids Vi, I = 1, . . ., c as shown below (i.e. eq.3)

$$v_{ri} = \frac{\sum_{k=1}^{n} u_{ik}^{m} \omega_{kr} I_{kr}}{\sum_{k=1}^{n} u_{ik}^{m} \omega_{kr}} \quad \ldots\ldots\ldots\ldots (3)$$

Step 7. In the event that the quantity of cycles is littler than Iter and $\sum_{i=1}^{c} \|V_i^{new} - V_i^{old}\| < \varepsilon$, go to stage 5; otherwise, go to step 8

Step 8. To expel the isolated misclassification focuses, membership matrix U (i.e. eq. 4)

$$\widetilde{u_{ik}} = \sum_{r\in N_k} u_{ikr} \times \omega_{kr} \quad \ldots\ldots\ldots\ldots (4)$$

Step 9. Get the section results with this new matrix of membership function U={u_i, i=1……c}.

3.4. Feature Extraction

Gray Level Co-occurrence Matrix (GLCM) is used to extract the texture feature. In a statistical texture analysis, texture features were computed on the basis of statistical distribution of pixel intensity at a given position relative to others in a matrix of pixel representing image.

Features considered are listed below:

3.4.1. Energy

Energy (E) can be characterized as the proportion of the degree of pixel pair recurrence (i.e. eq.5) It represents the similarity of a picture. When pixels are very similar, the energy value will be large.

$E=\sum\sum p(x,y)^2$ …….… (5)

P(x,y) is the GLCM

3.4.2. Contrast

The contrast (Con) is characterized as a intensity of a pixel and its neighbor over the picture (i.e. eq.6) In the visual approach of this present reality, contrast is controlled by the distinction in the shading and brightness of the object and different objects inside a similar field of view.

$I = \sum\sum (x-y)^2 p(x,y)$ …….… (6)

3.4.3. Correlation Coefficient

Measures the joint likelihood event of the predefined pixel pairs (i.e. eq.7). Returns a proportion of how related a pixel is to its neighbor over the entire picture.

Correlation: sum (sum $((x- \mu_x)(y-\mu_y)p(x , y)/(\sigma_x \sigma_y))$)

……. (7)

3.4.4. Homogeneity

Measures the closeness of the dispersion of components in the GLCM to the GLCM joining two opposite corners of a square(i.e. eq.8).

Homogeneity: sum (sum (p(x, y)/1+ [x-y])))

……. (8)

3.5. Classification using SVM

A Support Vector Machine (SVM) is a supervised machine learning algorithm that can be employed for classification. The original SVM algorithm was invented by Vladimir N. Vapnik and Alexey Ya. Chervonenkis in 1963.

Training sample in support vector machine is separable by a hyperplane. This hyperplane is computed according to the decision function f(x) = sign (w.x) + b, where w is a weight vector and b is a threshold cut-off.

To maximize the margin, w Є f and b have to be minimized to

Xi. w + b ≥ +1 for yi = +1

Xi . w + b ≤ -1 for yi = -1

Yi (xi . w + b) -1 ≥ 0

Additional slack variables should be added to prevent overfitting.

Xi. w + b ≥ +1 - ξ for yi = +1

Xi . w + b ≤ -1 + ξ for yi = -1

Yi (xi . w + b) -1 + ξ ≥ 0

A Support Vector Machine (SVM) is a discriminative classifier portrayed by a detaching hyperplane. As such, given named training information (supervised learning), the calculation yields an ideal hyperplane which classify new illustartion. Let's consider the following simple problem:

We are given a set of n points (vectors): x1, x2,..x3, xn such that xi is a vector of length m, and each belong to one of two classes we label them by "+1" and "-1". So our training set is

(x1, y1), (x2, y2), ….. (xn, yn)

$\forall$ I xi $\in$ Rm , yi $\in$ {+1, -1}

To find a separating hyperplane that separates these points into the two classes. "The positives" (class "+1") and "The negatives" (class "-1"). Let's introduce the notation (i.e. eq.9 and eq.10) used to define formally a hyperplane:

$f(\chi) = \beta 0 + \beta^T x$ ……. (9)

$\beta 0$ ……. (10)

Where,β is known as the weight vector and βo as the bias. For a linearly separable set of 2Dpoints which belong to one of two classes, find a separating straight line.

Then, the operation of the SVM algorithm is based on finding the hyperplane that gives the largest minimum distance to the training examples. Twice, this distance receives the important name of margin within SVM's theory. Therefore, the optimal separating hyperplane maximizes the margin of the training data.

The optimal hyperplane can be represented in an infinite number of different ways by scaling of β and βo. As a matter of convention, among all the possible representations of the hyperplane, the one chosen is

$|\beta 0 + \beta T \chi| = 1$ ……. (11)

Where $\mathbf{x}$ symbolizes the training examples closest to the hyperplane. In general, the training examples that are closest to the hyperplane are called support vectors. This representation is known as the canonical hyperplane.

The data usually contain noises, which result in overlapping samples in pattern space, and there may produce some outliers in the training data set. So we need to remove these outliers from the training data set so that a better decision boundary can be easily formed. We here apply smoothening method to remove those points that do not agree with the majority of their k nearest neighbors.

IV. EXPERIMENTAL RESULTS

The 43 CT images from the patients were trained to the system. Accordingly 10 new input images were taken and classified whether the oral cavity tumor is detected or not. There are mainly three performance parameters namely sensitivity, specificity and accuracy as shown in Table 1. The accuracy equals the sum of true positives and true negatives. It indicates the degree to which a segmentation algorithm results matches with

reference or ground truths (i.e. in Table 1). Specificity means the true negatives divided by true negatives and false negative. It indicates true negativity and it is the probability that a detected or segmented pixel does not belong to the tumor but it belongs to the background (i.e. in Table 2). Sensitivity means the true positive divided by true positive and false negative. It indicates true positivity and it is the probability that a detected or segmented pixel belongs to the tumor (i.e. in Table 3).

Accuracy= TP+TN/TP+TN+FP+FN……. (12)
Specificity = TN/TN+FN…… (13)
Sensitivity= TP/TP+FN…….. (14)

Where TP ⟶ 'True Positive' which is the number of pixels exactly detected as tumor pixels.
TN ⟶ 'True Negative' which is the number of pixels exactly detected as not tumor pixels.
FP ⟶ 'False Positive' which is the number of pixels wrongly detected as tumor pixels.
FN ⟶ 'False Negative' which is the number of pixels wrongly detected as not tumor pixels.

According to F.Abdolali, R. A. Zoroofi et al. [1] and Mascharak S et al. [23] , the highest accuracy obtained was 61.54% and 65.9%, the proposed solution improved the accuracy to 85%.

Table 1. Performance Analysis of Accuracy

Authors	**Accuracy**
F.Abdolali, R. A. Zoroofi et al. [1]	61.54%
Mascharak S et al. [23]	65.9%
Proposed	**85%**

According to Mascharak S et al. [23] and Sridhar G Reddy et al. [22], the highest specificity obtained was 64.9% and 81.25%, the proposed solution improved the specificity to 84.52%.

Table 2. Performance Analysis of Specificity

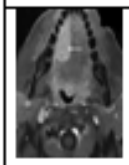
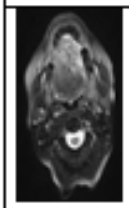
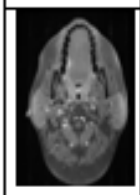
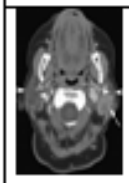
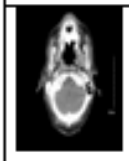
Authors	**Specificity**
Mascharak S et al. [23]	64.9%
Sridhar G Reddy et al. [22]	81.25%
Proposed	**84.52%**

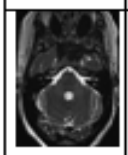
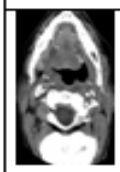
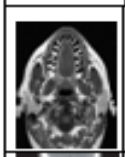
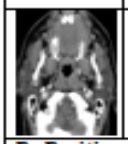
According to Mascharak S et al. [23], and Sridhar G Reddy et al. [22] the highest sensitivity obtained was 66.8% and 43.5% , the proposed solution improved the sensitivity to 85.82%.

Table 3. Performance Analysis of Sensitivity

Authors	**Sensitivity**
Mascharak S et al. [23]	66.8%
Sridhar G Reddy et al. [22]	43.5%
Proposed	**85.82%**

Table 4. Test results of accuracy, specificity and sensitivity

Original Image	Tumor Detected	Accuracy	Specificity	Sensitivity
	P	0.8524	0.9431	0.9548
	P	0.8361	0.9061	0.9223
	N	0.7648	0.7728	0.7795
	N	0.7653	0.7737	0.7806
	N	0.7674	0.7770	0.7848

Original Image	Tumor Detected	Accuracy	Specificity	Sensitivity
	P	0.8149	0.8618	0.8798
	N	0.7970	0.8278	0.8440
	N	0.7831	0.8031	0.8161
	P	0.8164	0.8649	0.8829
	P	0.8432	0.9218	0.9364

P= Positive ; N= Negative

V. CONCLUSION

The proposed method uses anisotropic diffusion filter for pre-processing images by removing the noise and enhancing the boundary. Then fuzzy c-means used to segment the image, followed with feature extraction by Gray-Level Co-Occurrence Matrix (GLCM) and classifying of the oral tumor by Support Vector Machine (SVM). In this, an efficient and suitable algorithm to improve the oral tumor accuracy of 85%, specificity 84.52%, sensitivity of 85.82%, especially tumors in the edge area and small tumors in the early stages of the disease is proposed.

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Vindya Shree M P" A Novel Method for Automatic Detection of Early Stage Oral Cavity Cancer" International Journal of Engineering Research and Applications (IJERA), Vol. 09, No.07, 2019, pp. 09-16