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Article

Detection of Pre-Cancerous Conditions in Oral Cancer Progression

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Abstract: —Cancer is one of the main causes of deaths globally, responsible for around 10 million deaths in 2020. This is attributable to the predominance of patients detected at late stages. mouth cancer is the most frequently diagnosed cancer in the world. The increased death rate is mostly related to late-stage diagnosis; prompt intervention on the identification of oral cancer or pre-cancerous lesions is expected to give improved results and reduce treatment expenses. The currently available diagnostic approaches include clinical examination, imaging, and the Light Gradient Boosting Machine (LightGBM) classifier. This research presents a unique method to differentiate among malignant and benign oral cancers and to detect their pre-cancerous stages. The proposed methodology introduces a hybrid DL model that incorporates MobileNetV2 along with a Support Vector Machine (SVM) classifier, and by using Histogram of Oriented Gradients (HOG) feature extraction. This extension utilizes deep feature representations acquired through MobileNetV2, by using HOG descriptors to identify edge and structural data pertinent to oral lesion patterns, in contrast with the original LightGBM-based framework that depends on manually extracted colour and texture features. The deep-HOG vector of features is used as input to an SVM-based classifier to improve the performance, particularly in multi-class situations. The study shows outstanding performance, more than the current state-of-the-art techniques. The proposed method provides an efficient and effective solution for the categorization of oral cancer.

Keywords: —oral carcinoma, fatality rate, precancerous lesions, Light Gradient Boosting Machine (LightGBM) classifier, hybrid deep learning architecture, MobileNetV2, Support Vector Machine (SVM) classifier, Histogram of Oriented Gradients (HOG) feature extraction.

1. INTRODUCTION

Cancer is recognized by uncontrolled cell growth and acquisition of some metastatic properties. In most of the cases, activation of oncogenes and/or deactivation of tumor suppressor genes leads to uncontrolled cell progression and inactivation of apoptotic mechanisms. Malignant cancers can capture metastasis, that occurs due to the down-regulation of cell adhesion receptors these receptors are necessary for tissue-specific cell–cell attachment, and up-regulation of receptors which enhance cell motility. opposite to benign tumours, the activation of membrane metalloproteases makes metastatic cancer cells to spread [1] by providing a physical pathway. Any atypical proliferation of cells that infiltrates to other regions of the body will be classified as cancer. The oral cavity extends inferiorly from the lip's vermilion border to the circumvallate papillae of the tongue and finally to the junction of the hard and soft palate superiorly. Oral cavity is divided into different types of subsites: lip, floor of mouth, tongue, buccal mucosa, hard palate, retromolar trigone, upper and lower gum [2].

The cavities of the mouth are primarily associated with surface tissue, where surface cells go through pre-malignant pathological alterations, these alterations gives the results of pre-malignant conditions that include leucoplakia erythroleukoplakia, and erythroplakia [4], which can progress to (SCC) Squamous Cell Carcinoma [5], which is approximately becoming the reason for ninety percent of all mouth cancers. Oral cancer shows an erytholeukoplastic area without any symptoms in its initial stages but as it gradually increases to advanced stages it shows lumps & ulcers that becomes rigid to even touch. To overcome these we need to establish different diagnosis methods which gives more prominent results than the typical OSCC [5]. Leukoplakia [3] refers to a flat, white, and elevated lesion that is not attributed to any specific pathological condition and ailment, without an identifiable underlying cause; nonetheless, associated risks also includes heavy use of tobacco and heavy consumption of alcohol. It is often devoid of discomfort and may be swiftly removed. Cellular-level leucoplakia has a thick keratinous coating that appears white when flat and demonstrates dysplasia, a pre-cancerous disease in microscopic level it is often identifiable.

This abnormally grown cells progressively turns into cancerous cells. As these abnormal cells exhibit heightened dysplasia, the lesions often manifest as red patches termed erythroleukoplakia [6]. Cells within the red region have sustained significant DNA damage and have become premature, rendering them incapable of producing keratin. Consequently, it becomes more fragile, and blood vessels may become visible through the mucosa, a condition referred to as erythroplakia, indicative of severe dysplasia or early-stage carcinoma. During the research study of some authors it is confirmed that 375 women were interviewed, and out of that 375 women only 28.5% of women know about this oral cancer. As we can see here 4 out of 10 women were aware of symptoms and 5 out of 12 women are aware of risk factors, and they lacking the general awareness of this oral cancer risks and symptoms. Some group of diseases which are originated from fallopian tubes and ovaries are comprised by oral cancer. Ovarian cancer affected 3,24,398 women globally In 2022, these resulting in 2,09,830 deaths within that year [7].

Compared to other places globally, the ovarian cancer issue is more pronounced in India, where 70% of cases are recorded at stages that are advanced The delay in discovery results in low odds of successful treatment, thereby leading to a significantly elevated death rate. Timely diagnosis and appropriate treatment might enhance the chance of survival rates to 90%. Consequently, user-friendly ovarian cancer diagnostic tools need is critical these tools should be rapid, non-invasive and precise [7]. The standard care is primary surgical resection it is done with or without postoperative therapy. Eventhough the early diagnosis is relatively easy, presentation with advanced disease is not uncommon. These uncommon advanced diseases can be cured with some Improvements in operational techniques. And if these techniques are combined with the postoperative radiation or chemoradiation therapy then it will resul in improved survival rates. On multidisciplinary treatment strategies, Successful treatment is predicated to increase oncologic control and reduce impact of the therapy on form and function. oral cancer requires better education about lifestyle-related risk factors to prevent and also need improved awareness and tools for early diagnosis [2].

Under the traditional methodologies applied, the diagnosis is contingent upon the clinician's knowledge and experience. Human diagnosis is susceptible to mistakes, and the absence of a clear measure to establish the threshold complicates and makes the classification of oral cavity conditions more subjective. Therefore, in the pre-identification of oral cancer an automated approach would significantly assist the community and reduce false-positive rates. Consequently, we are proposing a methodology that employs texture & colour characteristics from several colour spaces to categorize mouth cancer into its early-stage phases. Here to detect oral cancer we need a key element and that is texture, it is used widely in computer vision systems. For the eyes, finding the different textures is an easy task [11]. The texture is often referred to as recurring visual patterns present in the picture. A multitude of methodologies for textured feature extraction has been introduced throughout time, and the study field remains susceptible to many assessments. Recently, seven segments were proposed to classify the texture feature collection process. One is Statistical processes, graph-oriented processes, transform based procedures, structural processes, model-driven processes, entropy based procedures and learning-oriented processes [12].

In addition to texture, colour is a crucial element in human image perception and image processing. In contrast to intensity, that is represented as a scalar in gray colour pictures, colour is seen as a vector attribute assigned for each and every pixel in a coloured picture. Unlike grayscale photos, which may be handled using straightforward methods, colored images need a variety of processing techniques. Consequently [13], it is clear that one must ascertain whether to examine color and texture elements separately or to integrate them via a transformation for a combined analysis. Research on colored textured analysis has been limited, with most studies using grayscale texture analysis approaches.

The domains of (ML) Machine Learning as well as (DL) Deep Learning have significantly broadened in recent years, owing to technological advancements that facilitated data digitization, particularly in the context of patient information through digital case studies and imaging files, specifically in pathology & radiology. A modern concept is shown in the growing advantages of radiomics [14], which is a computational method that facilitates the identification and significantly alters imaging data processing to reveal distinguishing features imperceptible to the unaided eye. These distinctive imaging indicators may provide diagnostic, prognostic, and therapeutic advantages.

Machine learning and deep learning methodologies achieves significant results in categorizing mouth cancer lesions by their stages. Several prior studies using white light imaging are examined to detect the oral cancer. Including medical examination, imaging, and the LightGBM classifier. The dataset was very small for a classification with multiple classes task, since the core LightGBM-based system depends on manually designed color and texture characteristics, and further performance metrics beyond accuracy were not taken into account. The suggested technique integrates a hybrid model that combines MobileNetV2 plus a (SVM) Support Vector Machine classifier, augmented by Histogram of Oriented Gradients (HOG) feature extraction. It was determined that the integration of imaging modalities yielded superior outcomes compared to the separate methods. Nonetheless, the performance may have deteriorated due to the variability in the tissue architecture of the oral cavity.

2. RELATED WORK

The advancement of deep learning as well as machine learning are the current surge in the popularity of healthcare. it has been significantly influenced by education. Researchers have examined several frameworks to enhance medical assistance.

Nanditha et al. [18] identified oral cancers with machine learning along with deep learning methodologies. Oral cancer might be classified as a lethal illness. Timely identification of the condition facilitates swift recovery. This research's originality is in the use of deep neural networks with machine learning model. This study employs a 43-layer deep convolutional neural network (CNN). The data analysing findings indicate that the suggested technique demonstrates outstanding proficiency in formatting and recognizing CT scan pictures, hence effectively simulating dangerous oral lesions with precision.

Khanagar et al., [9]. evaluated that the efficacy of an AI technique in diagnosing oral diseases and forecasting disease prevalence. This research used artificial intelligence techniques to identify and forecast the disease's onset. Factors used in the diagnosis of the condition including age, sex, smoking status. The analytical findings indicated that the AI is providing an adequate evaluation of the input data, leading to a correct detection of oral cancer.

Panigrahi et al., [19]. examined a machine learning system using histological pictures of malignant oral lesions to detect oral cancers. Artificial intelligence is a very effective tool for identifying many illnesses, including cancer. This research used six prevalent ML techniques to determine the best fit technique for diagnosing oral lesions. These six techniques include (KNN) K-nearest neighbor, random forest, naive Bayes, (SVM) support vector machine, neural network, and decision tree. The strategy analysis process indicated that a neural network method achieved the best accuracy among the other techniques, having a score of 90.4%. The investigation indicates that this technique has a commendable capacity for illness diagnosis.

Metaheuristic algorithms have gained prominence in optimizing deep learning models. Pérez and Ventura (2022) [20] used a genetic strategy to enhance a combined CNN model to predict skin cancer diagnosis, with an accuracy of 92.8%. Their research underscored the efficacy of neural network algorithms in improving model performance [4]. The suggested model employs the truncate Swarm Algorithm (TSA) in hyper parameter optimization, demonstrating the capacity of metaheuristic methods to enhance convergence and mitigate overfitting.

Akilandasowmya et al. (2024) underscored the significance for deep feature extraction in improving combined models for skin cancer detection, attaining an accuracy of 92.9%. Their research revealed that the amalgamation of intricate data elements with ensemble methodologies might markedly enhance diagnostic efficacy. Likewise, the suggested oral cancer detection system rigorously preprocesses this ORCHID dataset to guarantee superior feature representation.

Prabhakar et al., [8] used neural networks to classify & identify mouth cancer. Medical professionals recognized several categories of oral cancer. A comprehensive examination of these oral cells may enable the prompt identification of both benign or malignant oral lesions. Various techniques exist for identifying malignant oral lesions. This research used a network that is linear to identify the type of lesion. The proposed methodology is evaluated with the help of information gathered from 75 ailing people. The findings revealed that the classification accuracy was around 85.19% for T2, 100% for T1, 94.12% for T4, and 84.21% for T3 phases, respectively.

Camalan et al., [18] used a CNN algorithm to identify multilayer carcinoma of squamous cells of the mouth. They used the Inception ResNet V2 methodology to classify the photos. for assessing the network's effectiveness in detecting carcinomas of squamous cells of the oral cavity with several layers, pictures from 54 individuals with oral lesions were used. The classification of cancerous lesions and processing of images demonstrated that this network attained an accuracy rate of 74% in detecting oral lesions. The data demonstrated that this proposed network is effectively used for the identification of oral diseases.

Jeyaraj et al., [17] utilized a deep CNN to identify medical pictures for the diagnosis of oral cancers.

Timely and precise diagnosis of malignant oral cancers may significantly facilitate prompt treatment of the disease. Various methods are available for identifying this disease. In their study, they used a CNN to diagnose the disease. The CNN's efficacy in evaluating malignant lesions was assessed by quantifying accuracy, & sensitivity. The accuracy is 91.4%, sensitivity is 94%, and specificity is 91%. The classification accuracy of oral malignant tumors was 95%. The findings revealed that the CNN might achieve good outcomes in diagnosing oral cancers. Furthermore, the CNN generated pictures of superior quality for illness detection.

3. DATASET DETAILS

The significance and caliber of a training dataset dictate the effectiveness of any medical intervention. The dataset for this work has a balanced mix of cancer-associated and noncancerous images, allowing effective training and testing of the deep learning system. The images were sourced from online databases, and freely available medical image repositories. These images shows several stages of oral cancer, including precancerous conditions, advanced malignant tumors impacting the lips, tongue, and oral cavity, as well as early-stage lesions.

Images of non-malignant conditions, including benign ulcers, normal mouth tissues, and other abnormalities that may mimic cancer forms, were also collected. The algorithm can precisely differentiate between malignant and non-cancerous instances due to this extensive dataset. Images captured from several perspectives, lighting conditions, and dimensions were used to ensure data variety, yielding a more generalized model applicable to real-world scenarios.

A designated folder named "Dataset" was established inside the project structure to contain the pre-processed dataset. after the collection of the dataset, the first round of preprocessing was to identifying and removing duplicate photographs. Frequent rescans or modifications in patient records can lead to duplicate pictures in healthcare imaging datasets, potentially resulting in model overfitting and biased learning. Methods for similarity identification and hash-based comparison techniques were used to recognize duplicate photographs. Here We are ensuring the dataset's integrity by eliminating duplicate samples, so preventing superfluous copies of data for training that may potentially manipulate model predictions. This step of model training minimizes computing resources and significantly enhances dataset's efficiency. Data augmentation was introduced to expand the dataset and improve the model's ability to generalize across various conditions after the removal of duplicates.

Augmentation methods used included rotation, flipping, zooming in, shearing, brightness adjustment, and the insertion of Gaussian noise. The model exhibited increased resilience to variations in lighting, positioning, and visual distortions due to these modifications, we are generating several iterations of the same picture. Data augmentation was very important to prevent overfitting by ensuring that the model focuses on generalizable features relevant to oral cancer diagnosis instead of image-specific patterns.

To facilitate the construction, and testing of this model, we have divided the dataset into two separate parts after preprocessing. The split was methodically crafted to make sure the system learned everything correctly from its initial training set despite being evaluated on unfamiliar data for performance assessment. Around 80% from the dataset was given for training the model, and the remaining 20% was given for testing. The testing dataset was used to test the model's performance, including the bulk data required for the model to identify significant patterns. The test set, entirely distinct to the training data, was being used to test the final model's predictive accuracy in real-world conditions.

4. PROPOSED METHODOLOGY

The suggested oral cancer detection system combines a deep learning model and a model using machine learning to provide real-time predictive results. The first phase of the system's process involves loading the dataset.

Oral cancer dataset is taken from Kaggle's healthcare dataset, which has thousands of labeled objects, including photos of symptoms, demographic details, and validated illness diagnoses.

Before processing each record, it is essential to ensure that the input information is sanitized by eliminating noise. In preprocessing, we must guarantee that the data set is consistent, devoid of noise, and ready for the model training, with the dataset divided into both training & testing groups. The primary aim of the preprocessing was to improve data quality, minimize noise, and uncover significant patterns.

The suggested system employs a pre-trained MobileNetV2 model that is based on CNN. It is a MobileNets design that use deeper separable layers to build lightweight DNN that enhance computational efficiency. MobileNets are much less in size and exhibit enhanced performance in mobile apps. They are used for categorization and detecting in mobile apps and devices because to their low latency and little power consumption. Their compact size renders them effective deep learning models & endows mobile devices with high-speed computing capabilities. This MobileNetV2 lightweight CNN model has primarily two blocks, one is a block with stride [1 1], which is often referred to as the residual block with S [1 1], and the other one is a block with stride [2 2], that primarily serves the purpose of downsampling. Depth wise convolution executes filtering that is inherently light. It is accomplished by using a single convolutional filter for each input channel, constituting the very first layer in the block of MobileNetV2. The 1×1 convolution layers constitutes MobileNetV2 block's second layer & it is referred to as the point-to-point convolution. The 1×1 convolutions facilitate the organization of additional features via the linear amalgamation of input data channels. The MobileNetV2 convolutional neural network model was extensively used in hospitals for medical image processing.

We are integrating the MobileNetV2 system with a (SVM) support vector machine technique. SVC uses a kernel that is linear to independently trained on feature sets derived from mobileNetV2, emphasizing binary classification. We are using the linear kernel because of its easy use, particularly in multiclass classification problems, here the main objective is to distinguish between two classes first one is presence of dysplasia and the other class is absence of dysplasia with a distinct border. In multidimensional featured data, a linear kernel excels by supposing the data points are separated linearly, that corresponds along with prerequisites of binary and multiple classifications in medical imaging. Here this method guarantees efficiency in computations and mitigates danger of overfitting, this makes it especially appropriate for issues like for situations where class relationships may be delineated by linear bounds. The explicit decision making procedure of a linear kernel model in further augments its efficacy for binary and multiclass seperation, delivering strong performance while preserving clarity in medical significant tasks.

A Support Vector Machine using a linear kernel has been trained on the characteristics derived from MobileNetV2. Due to MobileNetV2's ability to capture intricate local networks, the SVM demonstrates strong performance on almost every class (the presence of dysplasia), effectively detecting distinct dysplastic pattern with high sensitivity. This increased sensitivity guarantees precise identification of diseased tissues, hence reducing the likelihood of negative results, which may have significant clinical consequences.

The combined use of mobileNetv2 features and SVM classification is a formidable strategy for harnessing the advantages of deep learning and conventional ML methodologies. The proposed hybrid model attains excellent accuracy outcomes, by concentrating on intricate morphological characteristics.

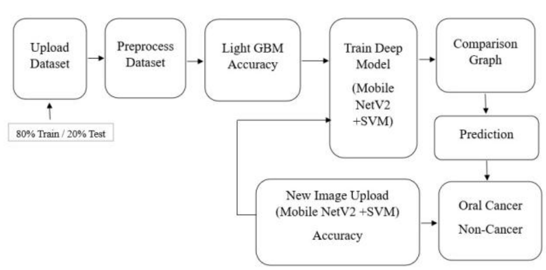

Figure 1: Framework for the hybrid model mobileNetV2 and SVM

5. RESULT AND DISCUSSION

We evaluated a hybrid model that combines MobileNetV2 with SVM for the classification of oral cancer. During the training phase of InceptionResNet-v2, early stopping was not used for deep feature extraction. Both models underwent training. so providing uniform training circumstances will enable equitable comparisons.

The model has been trained and verified using a medical dataset of over 10,000 records including several kinds of oral cancer via symptom-disease mapping. Each record has details about the symptoms and their intensity. Figure 2 presents a collection of photos from the dataset, depicting various manifestations of oral cancer, while Figure 3 features another dataset exhibiting the appearance of a healthy mouth devoid of oral cancer.

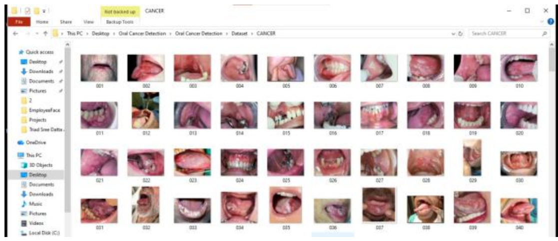

Figure 2: A Selection of Records of cancer from the dataset

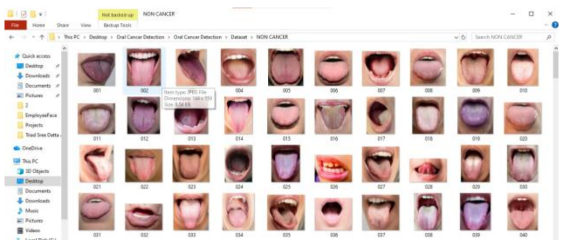

Figure 3: A Selection of Records of non cancer from the dataset

The input data underwent preprocessing to extract characteristics from the photos, including methods like scaling, improvement in contrast, reduction in noise, and normalization. The dataset was divided into two parts, one is used for training and the other one is used for testing, with an 80:20 ratio, this partition enhances the model's performance.

Performance of hybrid deep learning Model

The hybrid deep neural network model had been trained to extract features from picture inputs with MobileNetV2. It is also taught to classify oral cancer data via (SVM) support vector machines. The system achieved an accuracy rate of 92.11% when given unseen test data, with recall, precision, and F1-score values of 93%, 92.08%, and 92.54%, respectively. Figure 4 illustrates the ROC curve, demonstrating a robust discriminative ability with an (AUC) area under the curve of 0.96. Additionally, Figure 4 presents a comparative graph depicting the metrics of accuracy, recall, precision, and F1-score for both the existing LightGBM system and the proposed hybrid deep learning model.

Figure 4: Comparison graph between LightGBM and MobileNetV2 + SVM

Following the analysis of the comparison graph, we have decided to use the MobileNetV2 combined with the SVM model for predictions. As seen in Figures 5 and 6, the model classifies the picture inputs as either cancerous or non-cancerous. Likewise, we may provide an alternative picture input to ascertain if it depicts cancerous or non-cancerous tissue.

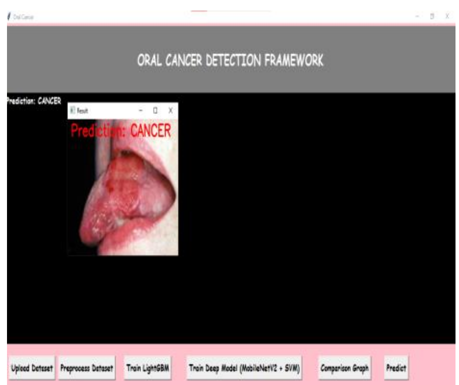

Figure 5: Predicted results for cancer

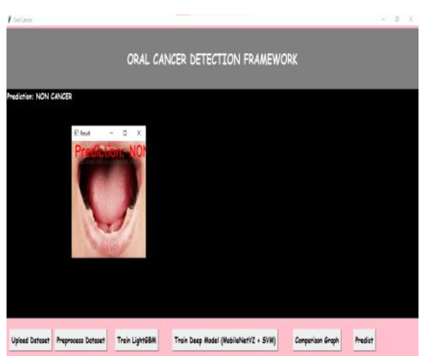

Figure 5: Predicted results for non cancer

Comparative Performance Summary

The categorization of oral cancer images was evaluated using Deep Learning methods such as MobileNetV2 & ML techniques such as (SVM) Support Vector Machine. Here the below Table 1 shows the performance metrics, indicating how well mobileNetV2 + SVM-based model outperformed baseline methods such as LightGBM.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Light GBM	86.17	83.96	90.82	87.25
Hybrid Deep Learning model (MobileNetV2 + SVM)	92.11	92.08	93.00	92.54

Table 1: Model evaluation Metrics

6. DISCUSSION

The proposed Hybrid model (MobileNetV2 + SVM) gives greater performance for the categorization of oral cancer. The likelihood of erroneous predictions is reduced due to the model's increased accuracy and F1-score, indicating its efficacy in distinguishing between oral cancer types. The comparison graph offers further proof of precise categorization ability.

Unstructured data inputs and ambiguous or hazy oral cancer photos may provide challenges for the algorithm. Employing ensemble deep learning techniques facilitates the identification of diverse lesion kinds and cancer stages, while also permitting the enhancement of the system onto a cloud-based or mobile platform, enabling dentists, physicians, and rural health practitioners to conduct screenings via smartphones.

7. CONCLUSION

Early identification of mouth/oral cancer is very important for attaining good patient results. The use of (CAD) computer aided diagnostic systems may assist doctors and medical professionals in detecting oral/mouth cancer in its early phases, using computer algorithms for analysing medical pictures. This early discovery enables prompt intervention and treatment, leading to improved results and perhaps preventing deaths. Computer aided diagnostic methods are extensively used for the identification of oral cancer. Consequently, enhancing the precision of a (CAD) computer aided design system was increases as a significant study domain. A machine learning & deep learning method (MobileNetV2 + SVM) was subsequently presented. The suggested approach is applied for Oral Cancer image (OCI) dataset, and its findings were compared with those of other state-of-the-art methods, including LightGBM, MobileNetV2, and SVM, to demonstrate the method's efficacy. The suggested technique integrates the mobileNetV2 & SVM algorithms to improve the precision and efficacy of oral cancer prediction and identification. The approach has an accuracy of 92.11% and a precision of 92.08%, demonstrating its capability to reliably categorize positive samples. The extremely high score for F1 of our suggested model, 92.54%, underscores the reliability of the methodology presented. The final findings demonstrated that the proposed strategy yields the most favorable outcomes. The suggested technique delivers an optimum system for diagnosing oral cancer from photographs, serving as a vital resource for physicians and medical professionals. Its increased accuracy and sensitivity facilitate the detection of probable malignant tumors, even in modest or incipient situations.

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