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White Light Image Analysis for Oral Cancer Staging: A Matlab Approach to Pre-Cancerous Detection

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ABSTRACT: Oral cancer is one of the most prevalent and deadly cancers globally, often diagnosed at an advanced stage. This project presents a MATLAB-based approach to detecting precancerous stages of oral cancer through white light image analysis. Using neural network classification (BPNN), the system identifies abnormal tissue regions with high accuracy. The proposed method aims to reduce human error in diagnosis by automating detection and staging through image preprocessing, segmentation, and feature extraction.

KEYWORDS: Oral Cancer, White Light Imaging, MATLAB, Neural Network, Image Processing, BPNN

I. INTRODUCTION

Oral cancer contributes significantly to global cancer-related deaths, with over 300,000 deaths recorded annually. It is aggressive and often diagnosed late due to asymptomatic early stages and limitations in current diagnostic practices. Traditional diagnosis involves biopsy followed by microscopic analysis, which is both time-consuming and prone to inter-observer variability. Recent advancements in image processing and machine learning offer alternative methods for automatic detection and staging. In this project, we propose a system that analyzes white light oral cavity images using MATLAB to classify tissue into normal, precancerous, and cancerous stages, reducing the dependency on manual diagnosis and enhancing early detection.

II. LITERATURE SURVEY

Any abnormal growth of cells that invades and spreads into other parts of the body could be termed cancer [1]. Oral cancer (OC) is a variety of cancer that develops in the oral cavity that includes the gingiva(gums), buccal mucosa, floor of the mouth or under the tongue, lips, anterior part of the tongue, hard palate, retromolar trigone and may spread to the oropharynx as well, the next part of oral cavity consisting of the walls of the throat, back part of the tongue, soft palate and tonsils [2]. The oral cavity and oropharynx are mostly linked with epithelial tissues, epithelial cells undergo pre-malignant pathological changes and form some typical pre-malignant lesions such as leukoplakia, erythro-leukoplakia, erythroplakia that develop into Squamous Cell Carcinoma (SCC) [3] which constitutes roughly 90% of all oral cancers. Leukoplakia is a white, flat and raised patch that cannot be characterized by any pathological disease or disorder with no apparent underlying cause but the risk factors include tobacco and excessive alcohol abuse. It is usually painless and could be quickly scrapped away [4]. Cellular-level leukoplakia shows a thick keratin layer that looks white when it's flat and shows some dysplasia which is a pre-cancerous condition distinguishable generally at the microscopic level. These dysplastic cells gradually grow into malignant cells. As cells become increasingly dysplastic, the lesions generally develop red spots known as erythro-leukoplakia. Cells in the red area have suffered severe damage to their DNA and become premature and, therefore, cannot produce keratin. As a result, it gets more delicate and blood vessels could be perceptible through the mucosa known as erythroplakia, which is severe dysplasia or early cancer [5]. Globally OC has the sixth rank when compared to other cancers. India on the other hand has the most significant number of OC cases, about one-third of the entire load globally [6]. Analogized to other regions of the world, the crisis of OC is more in India because 70% of the cases in India are reported late in the advanced stages (American Joint Committee on Cancer, Stage III-IV). Due to the delay in detection, the chances of getting cured are negligible, leading to a very high mortality rate [7]. Early diagnosis and proper treatment could improve the survival rate to 90%. Therefore, there is a serious need for OC diagnosis techniques that are easy to use, fast, accurate and non-invasive [8], [9]. For the detection of OC, initially the primary traces of the abnormal tissues of the oral cavity are adequately observed by a dentist. Upon surmise of some potential malignancy, it is further referred to an oral or maxillographic surgeon to conduct further tests

[10]. However, in the conventional techniques used, the diagnosis is subjective to the knowledge and expertise of the clinician. Human diagnosis may be prone to errors, and with no definitive parameter to set the threshold, it becomes more difficult and subjective to classify the oral cavity condition. Hence, an automatic system would greatly help the community with the early identification of OC and lessen false-positive rates. Therefore, we propose a method that uses color and texture features from different color spaces to classify oral cancer into its pre-cancerous stages. Texture features are foremost in segmentation, classification and synthesis of images. However, a fixed definition of texture is yet to be considered. The texture is usually termed as repetitive visual patterns appearing in the image. Numerous techniques are presented over time for texture feature extraction and the research arena is yet vulnerable to many analyses [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]. Newly, seven segments were suggested to categorize the texture feature extraction procedure [11]: statistical procedures (for instance, the co-occurrence matrices), structural procedures, transform-based procedures (Fourier transform-based procedures, and a few others), model-based procedures (random field models), graph-based procedures (local graph structures), learning-based procedures, and entropy-based procedures. Apart from texture, color is also an essential aspect of human perception of images and image processing [21], [22], [23], [24], [25], [26], [27]. Unlike intensity which is summarized as scalar in grayscale images, color can be seen as a vectorial feature that is fixed to each pixel of a colored image [21]. In disparity with grayscale images that could be processed in simple elementary ways, colored images could be processed in diverse ways. Thus, it becomes evident to determine the need to study color and texture features individually or both should be combined using some transformation and studied together [21], [27], [28]. Limited research has been conducted on colored texture analysis, most of the studies carried out were conducted by assimilating the application of grayscale texture analysis methods [29], [30], [31], [32]. The application areas of Machine Learning (ML) and Deep Learning (DL) have expanded vast in the past few years due to the technological advances that created opportunities for data digitization which became helpful in digitizing the data of patients through electronic case narratives and image files especially in pathological and radiological areas. A contemporary principle can be seen in the increasing benefit of radiomics, a computational standard that assists in manifesting the detection and radically influences imaging data transformation to catch the discriminatory characteristics not noticeable to the naked eye. Such unique imaging markers may be of diagnostically, prognostically, and restoratively beneficial [33], [34], [35], [36], [37], [38]. ML and DL approaches have achieved notable success in classifying oral cancer lesions into their stages. Some previous works that used white light images for detecting oral cancer are discussed. Thomas et al. [39] extracted texture discrimination features such as Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run-length Matrix (GLRM) and adopted a Back Propagation based Artificial Neural Network (BPANN) for classifying the tissues of the oral cavity into six categories such as Carcinoma Retromolar area as Group 1, Carcinoma angle of mouth –ulcero-proliferative as group 2, Verrucous carcinoma buccal mucosa as group 3, Carcinoma Buccal mucosa – Ulcero-proliferative as group 4, Carcinoma Tongue – lateral border of the tongue as group 5 and Carcinoma Palate – Ulcero-proliferative growth as group 6. The performance was considerable and increased by combining both GLCM and GLRM features. However, the dataset contained only 16 images, which is very diminutive for a multi-class classification problem, and other performance matrices other than accuracy were also not considered. Song et al. [40] captured whitelight and autofluorescence images using a low-cost, dual-modality, intra-oral screening device and used them to classify oral dysplasia and malignancy among patients. Different DL techniques based on Convolutional Neural Network (CNN) such as VGG-CNN-M, VGG-CNN-S, and VGG-16 were tested and it was concluded that the fusion of modalities of imaging produced better results than the individual ones. Nevertheless, the performance potentially degraded because of the variation in the tissue structure of the oral cavity. Welikala et al. [41] adopted a novel strategy in which bounding box annotation from multiple clinicians was considered. Further, a Deep Neural Network was used to build an automated system that extracted critical patterns for classification. Two DL computer vision-based techniques, ResNet-100 and Faster R-CNN were used to automatically detect and classify the oral lesion into six sub-groups. However, the accuracy was not considerable and some data annotations were not appropriately done. Fu et al. [42] used a Cascaded CNN-based classifier to detect Oral Squamous Cell Carcinoma (OSCC) that acquired high performance in various scenarios, including early detection and real-time smartphone application. However, the classifier could not generalize other types and areas of oral diseases in the oral cavity. Song et al. [43] developed an easy-to-use android smartphone application that implemented mobile-based dual-modality image classification for differentiating normal, potentially malignant and malignant lesions. An end-to-end dual-modality deep convolutional neural network was implemented for the automatic classification of dysplasia and malignancy images. However, the accuracy and time consumption was inversely inter-dependent, and a trade-off was needed between the two to get a considerable outcome. Lin et al. [44] developed a smartphone-based classifier to classify white light images into five categories of OC. The recent HRNet, trained on ImageNet, was validated on the collected image dataset with five data categories and the performance was acceptable. However, image acquisition is complex and requires domain knowledge. Nanditha et al. [45] considered a

dataset with a considerable size of well-annotated oral lesions and used machine and deep learning models to build an automated diagnosis system for classifying the lesion into benign or malignant. Classifiers such as Naive Bayes, K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Artificial Neural Network (ANN) and CNN were explored, and the results were compared. Also, a new CNN classification model was proposed that served as the new state-of-art for the classification task. Prachi et al. [46] developed a method for classifying normal tissues, leuko-plakia and erythroplakia where RGB and YCbCr color spaces were considered and corresponding the box plots of red and Y color components, a threshold is estimated to divide the lesions into categories. Later, texture features were derived using the Gray Level Co-occurrence Matrix (GLCM) to make the final decisions. The efficiency was notable but could not generalize all the types of lesions due to the presence of both white and red regions. Also, the proposed model could not perform efficiently for both binary and multi-class classification. Kevin et al. [47] introduced a two-stage segmentation and classification approach for OC detection. Random oversampling of the data, followed by data augmentation was carried out to increase the number of samples. Finally, a CNN-based network Guided Attention Based Inference Network (GAIN) was considered for the classification and segmentation of OC images. GAIN network works on three streams for achieving the goal, classification stream for classification of the samples, attention mining stream for generating the attention maps and bounding box stream for improving accuracy through pixel-to-pixel supervision. The performance achieved was acceptable and GAIN could effectively show the affected regions. However, performance could be further improved and data duplication was carried out to solve the issue of class imbalance, followed by data augmentation on the duplicated data, which may have led to over-fitting. Also, there was no external validation considered for validating the proposed architecture. Song et al. [48] evaluated the performance of remote and onsite diagnosis of OC. The evaluation was done for specialists evaluating patients on-site and remotely compared to AI-based diagnosis systems. A CNN-based architecture, MobileNet, pre-trained on ImageNet was used for on-device diagnosis on a smart-phone device, which required no external resources. Again, another module was developed for cloud-based diagnosis considering the Bayesian Deep Learning (BDL) network trained using VGG19. The adaptive histogram equalization technique was utilized to improve the brightness and contrast of the input images in the pre-processing step. However, the performance was not acceptable compared to the diagnosis of the specialists and dual-modality images were not combined to produce better outcomes. Warin et al. [49] evaluated numerous DL algorithms for OC diagnosis considering white light images of normal, OPMD and OSCC lesions. For the classification of OC lesions, DenseNet-169, ResNet-101, SqueezeNet and Swim-M Transformer were considered. For multi-class detection of the lesions, faster R-CNN, YOLOv5, RetinaNet and CenterNet2 were considered. Pre-trained model using transfer learning was considered except for SqueezeNet and Swim-S Transformer, which were trained from scratch. Also, attention maps for the affected regions were generated. The performance stood adequate for OPMD and OSCC classification from normal tissues but no external validation or cross-validation was considered for validating the model, and classification and detection were also considered independently. Al Duhayyim et al. [50] introduced a diagnosis system for the detection of oral cancer as benign or malignant from white light images, where a fusion-based feature extractor was considered and passed into an extreme learning machine (ELM) for categorization. The performance was notable but efficacy could be further improved and the issue of overfitting also needs to be clarified. Flugge et al. [51] developed a DL architecture based on Swim-Transformer for detecting OSCC. Also, gradient-weighted class activation (Grad-CAM) was applied to generate visual explanations, highlighting the important regions for classifying OSCC. The performance was satisfactory but neither validation was done on external datasets nor cross-validation was considered. Begum et al. [52] implemented a DL-CNN based technique to focus on the cancerous regions of the lip, tongue and cheeks and classify them to be cancerous or not. For this, a region proposal network (RPN) was proposed to extract the region of consideration which were then classified using a DenseNet201-based classifier. The performance was considerable but only accuracy as a metric was considered which cannot be completely acceptable when dealing with the diagnosis of cancer. Pahadiya et al. [53] proposed an algorithm for the segmentation and classification of tongue cancer using CNN. Initially, image enhancement techniques such as Histogram equalization, contrast stretching and sharpening were considered for image enhancement, after which the Gabor filter was considered to remove the unwanted noise present. Consequently, hybrid algorithms such as Firefly K-Means Watershed (FKW), and Hybrid Particle Swarm Optimization and Firefly K-Means Watershed (HPSOFKW) were implemented for segmenting smaller affected tissues and a comparison between the algorithms was highlighted. Finally, a two-layer CNN model was developed for classifying the segmented regions. Validation accuracy was considerable, but other performance metrics essential for biomedical image classification were not considered. Furthermore, there was no testing conducted on data that had not been previously seen, nor was there validation performed using an external dataset or cross-validation. Talwar et al. [54] aimed to evaluate DL algorithms for early diagnosis of OC. CNN architectures such as VGG19, Inception-ResNet-v2, MobileNet-v2, DenseNet-121, DenseNet-169, DenseNet-201 and transformer architectures such as Vanilla Vision Transformer (VVT), Data-Efficient Transformers, Swim Transformers

were evaluated in this work. A 5-fold cross- validation was considered and heatmaps for the affected regions were generated for better visualization. The performance was considerable for DenseNet-201 in the case of CNN-based architecture and Swim Transformer for transformer-based architectures. However, the performance decreased when tested on images captured by non-trained front-line health workers (FLHWs) which shows the lack of generability in the model for the task. Also, due to the complexity and high resource requirements, these networks could not be considered for real-time applications. It is observed from the literature survey that there is an essential need for a non-invasive technique for the diagnosis of OC in real-time with acceptable performance and negligible false positives. It is also observed that separate color spaces are significantly less explored. Also, colored texture features are significantly less explored while considering the white light images in OC classification. Therefore, in this paper, we aim to develop a technique for the classification of OC into its pre-cancerous stages using white light images to reduce the bias among physicians and classify the lesion in real-time with nominal resource utilization.

III. METHODOLOGY

The methodology is broken down into several stages:

A. Image Acquisition

- Images are collected under uniform white light using standard imaging devices.
- Dataset includes both healthy and pathological oral tissue images.

B. Preprocessing

- **Noise Removal:** Median filter or Gaussian filter to remove background noise.
- **Contrast Enhancement:** Histogram equalization to improve image clarity.

C. Segmentation

- **Thresholding:** Otsu's method used to separate lesion from background.
- **Edge Detection:** Sobel/Canny operator to highlight lesion boundaries.
- **ROI Extraction:** Region of interest identified for feature analysis.

D. Feature Extraction

Key features extracted:

- **Texture features:** Entropy, contrast, homogeneity, energy (using GLCM).
- **Shape features:** Area, perimeter, eccentricity, solidity.
- **Color features:** Mean RGB, HSV values of the ROI.

E. Classification Using BPNN

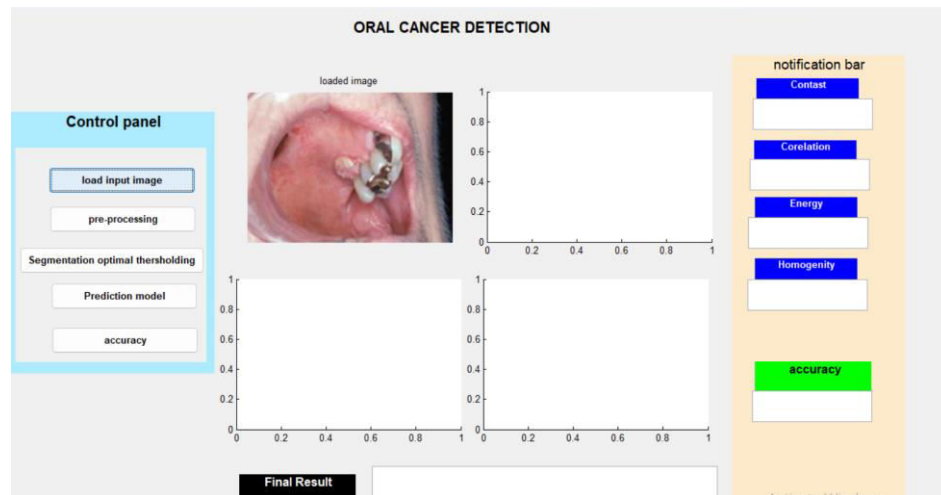
- A Backpropagation Neural Network is trained using extracted features.
- Dataset split into training and testing sets (e.g., 80:20).
- Output classes: Healthy, Pre-cancerous, Cancerous.
- Model is evaluated based on accuracy, sensitivity, and specificity.

IV. EXPERIMENTAL RESULTS

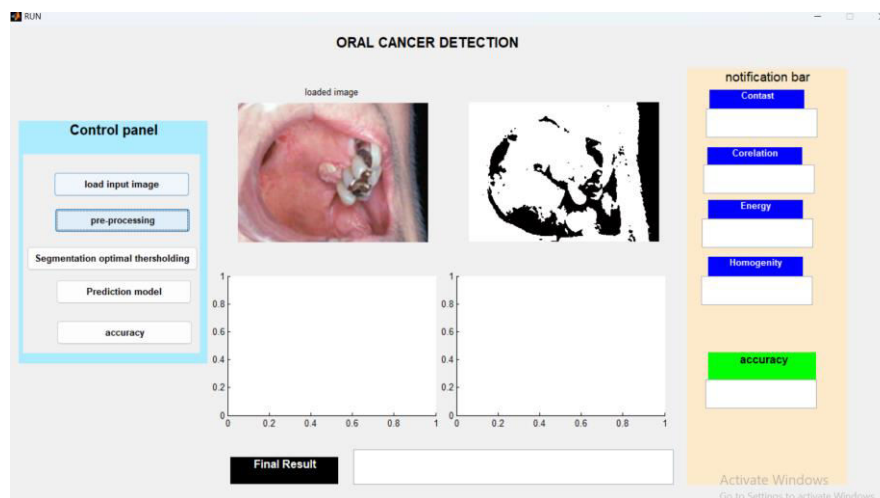
DATA SET



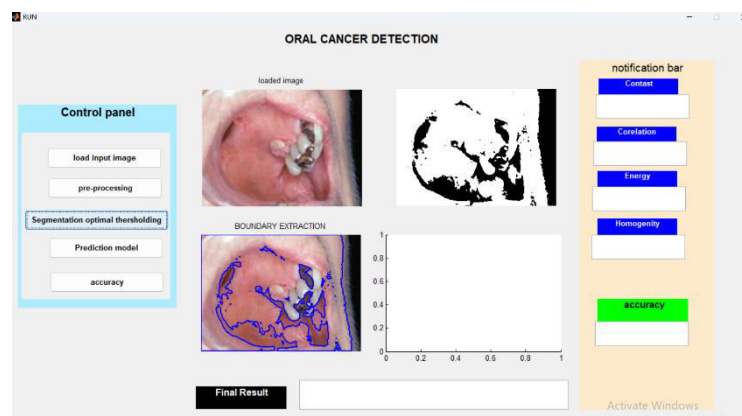
INPUT IMAGE



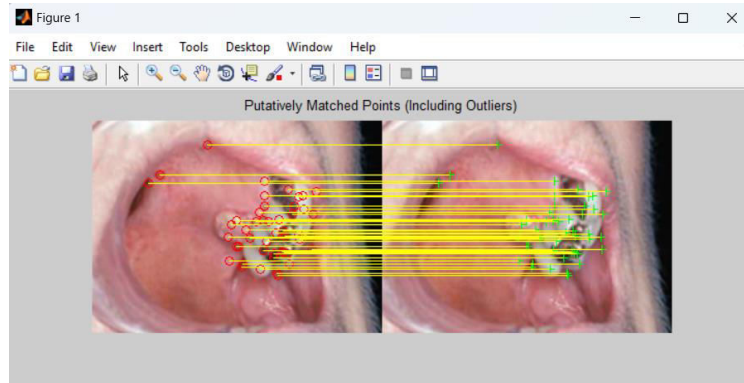
PREPROCESSING



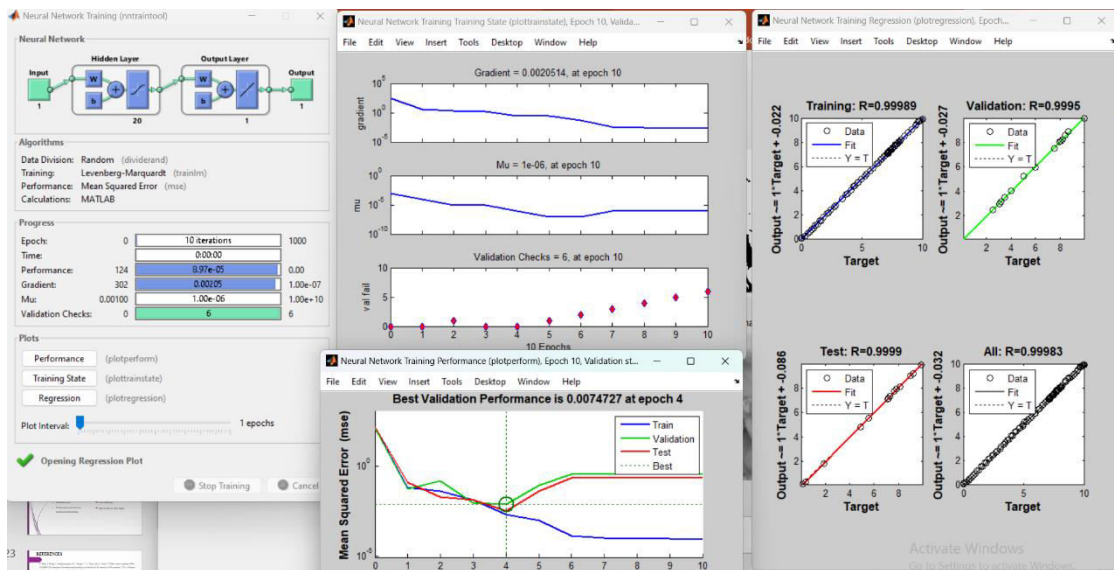
SEGMENTATION



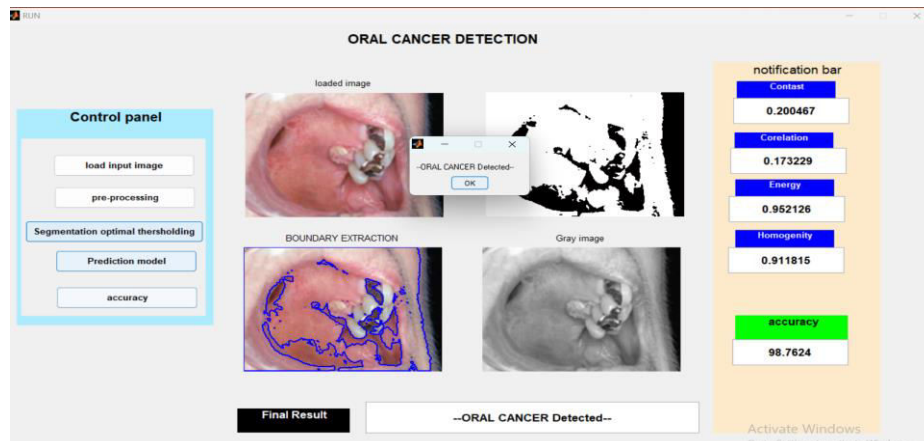
MATCHING POINTS



PREDICTION MODEL IN GRAPHS



FINAL RESULT WITH ACCURACY



V. CONCLUSION

This project demonstrates the potential of MATLAB-based white light image analysis for early detection and staging of oral cancer. By using a BPNN classifier trained on extracted texture and color features, the system achieves high accuracy and consistency. It is a promising decision-support tool for clinicians and can be extended to real-time diagnosis in the future. Further work can include fluorescence imaging, deep learning approaches, and larger datasets for improved robustness.

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