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Automated Detection and Classification of Oral Pre-malignant and Malignant Lesions Using AI Techniques

Vidhi Chaudhari[1], Dr. Hitesh Patel[2], Dr. Lokesh Gagnani[3]

[1]Research Scholar, Department of Computer Engineering, Kadi Sarva Vishwavidyalaya (KSV), SVKM, Gandhinagar, Gujarat, India.
E-mail: vidhichaudhary21@gmail.com, ORCID: https://orcid.org/0009-0007-0996-4905
[2]Associate Professor, Department of Computer Engineering, LDRP-ITR, Kadi Sarva Vishwavidyalaya (KSV), SVKM, Gandhinagar, Gujarat, India.
E-mail: hiteshpatel_ce@ldrp.ac.in, ORCID: https://orcid.org/0009-0003-6577-4285
[3] Associate Professor, Department of IT Engineering, LDRP-ITR, Kadi Sarva Vishwavidyalaya (KSV), SVKM, Gandhinagar, Gujarat, India.
E-mail: gagnani.lokesh@gmail.com, ORCID: https://orcid.org/0000-0001-6637-7319

Abstract
Oral cancer is one of the most prevalent cancers in the world and has a high mortality rate, primarily as a result of late diagnosis. Early identification of premalignant lesions such as leukoplakia and erythroplakia can greatly increase the survival rate; however, traditional diagnostic techniques are based on visual perception and biopsy examination, which are subjective, invasive, and time consuming. This work presents a fully automated AI system for the detection and classification of oral premalignant and malignant lesions. A set of clinical oral lesion images were gathered from publicly available medical repositories covering precancerous lesions and malignant types e.g., Oral Squamous Cell Carcinoma (OSCC), verrucous carcinoma, sarcoma, lymphoma, malignant melanoma, metastatic lesions. In order to handle data deficiency and class imbalance, we used several data augmentation methodologies such as rotation, horizontal flipping, brightness and contrast adjustment, scaling and Gaussian blur. The images were pre-processed by resizing, normalization, noise filtering and contrast stretching. The convolutional neural network model EfficientNet-B0 was used for feature extraction and the similarity-based k-Nearest Neighbors (k-NN) is employed for classification. An ensemble strategy was further employed by integrating complementary feature representations to improve classification robustness and accuracy. The highest score for predicted categories of lesions are displayed and then saved to a local database.

Keywords: Oral Premalignant Lesions, Medical Imaging, Computer-Aided Diagnosis, Oral Cancer.

Introduction

Oral cancer is a major global health problem, with oral squamous cell carcinoma (OSCC) responsible for about 90% of all oral cancers and ranking as the sixth most common malignancy in the world [1]. The 5-year survival rate for oral cancer is still only 50-60%, and this has not improved much over the past few decades, mainly due to the late diagnosis and presentation of patients with advanced disease [2]. Oral potentially malignant disorders (OPMDs), such as leukoplakia, erythroplakia are recognized as important risk factors for malignancy, but their evaluation is prone to considerable inter- and intra-observer variation among observers [3].

Recent developments in the field of Artificial Intelligence and Deep Learning have improved the detection and classification of oral premalignant and malignant lesions. Deep Convolutional Neural Net-works have been successfully used for the histopathological images of Oral Squamous Cell Carcinoma (OSCC) to differentiate between can-cerous and normal tissues, and to aid in pathological diagnosis by recognizing microscopic patterns that are not perceivable by human eyes [4]. Optimized CNN models have also shown effective performance in the detection of oral cancer from clinical images, which stresses the need for early diagnosis to ensure better treatment outcomes [5]. Comparative analyses of various CNN models have shown accuracy rates of over 95% in the classification of oral dysplasia and OSCC, which indicates the effectiveness of light models like MobileNetV2 in medical imaging applications [6]. Systematic reviews also support the fact that deep learning models show high diagnostic accuracy, with accuracy rates ranging from 85% to almost 100% in various studies [7]. Efficient models like EfficientNet have also shown high potential in distinguishing malignant tissues from normal oral epithelium in histopathological data [8]. These studies have also investigated mobile and practical screening applications. Deep learning algorithms like OralSegNet have shown excellent segmentation performance for oral lesions from smartphone camera images, which can aid community-level screening programs [9]. CNN-based screening systems have shown excellent performance for the identification of oral white lesions, including potentially malignant dis-orders, from photographic images [10]. Transfer learning algorithms like EfficientNet-B3 have enhanced diagnostic performance for OSCC screening while considering the variability in manual screening [11]. AI-powered screening systems incorporating DenseNet and InceptionV3 models have shown excellent performance for oral cancer diagnosis [12]. Moreover, multiclass deep learning models that can identify healthy, benign, potentially malignant, and malignant lesions suggest the possibility of an all-inclusive automated screening system [13].

Background & Objective

Oral cancer is a major public health issue in developing countries as they often lack adequate facilities for modern cancer treatment. Early lesions have subtle manifestations that are difficult to assess with routine inspections, possibly resulting in delays in diagnosis and poorer survival rates. Objective: The aim of this study was to develop a scalable automated classifier that is capable of diagnosing oral premalignant and malignant lesions using clinical oral lesion images. Such a classifier would enable detection of these lesions at an early stage, thereby allowing primary care screening in low-income and middle-income countries. Clinical oral lesion images comprising oral premalignant and malignant stages were collected from publicly available medical literature. Data augmentation methods such as rotation, flip, brightness and contrast adjustment, true size scaling, and Gaussian blur were used as well for generalization and tackling class imbalance. Images were resized to (224,224), normalized, denoised, and contrast-improved. The classification used transfer learning models, EfficientNet-B0 and ResNet50, which extracted relevant features from the lesional images. These features were then classified based on their similarity, using the widely-used k-Nearest Neighbors (k-NN) machine learning classifier. The system outputs predicted lesion classes with confidence measures and stores them in a local database. Results: The hybrid models combining EfficientNet-B0 and ResNet50, and k-NN, were able to classify oral lesions into premalignant and malignant lesions. Data augmentation assisted in enhancing the robustness of the model and minimizing the risk of overfitting. The model was able to differentiate between various types of Premalignant and malignant lesions. The proposed AI system is a non-invasive, accurate, and scalable solution for the early detection of oral premalignant and malignant lesions. The addition of advanced transfer learning models enhances feature representation and classification. The proposed system can be used to assist doctors in the early diagnosis and decision-making process, particularly in resource-poor settings.

Proposed Methodology

The proposed methodology consists of the following steps:

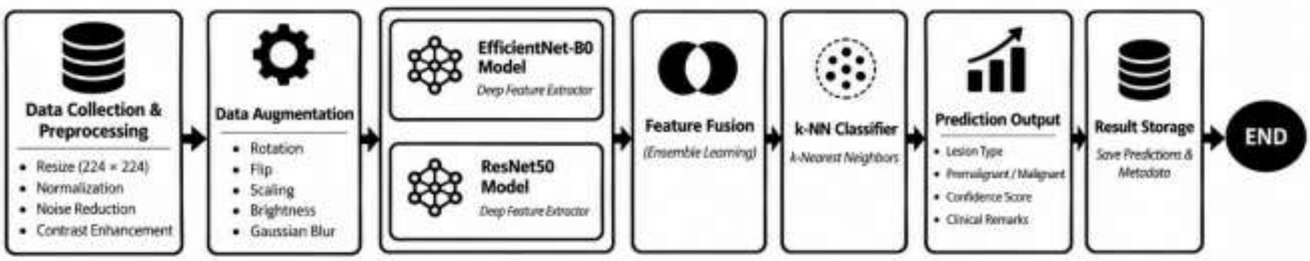

Figure. 1 Proposed Methodology flow chart

Study Design

An artificial intelligence (AI)-based automated system for the identification and classification of oral premalignant and malignant lesions is developed in this study using a data-driven experimental design approach. Aiming for this, the pro-posed study focuses on clinical images to propose a new non-invasive diagnostic support system for oral cancer detection including deep learning algorithms in accordance with recent AI-based medical imaging concerning [14].

Data Collection

Clinical oral lesion images were collected from publicly available medical sources, open-access databases, and published research articles. The dataset included premalignant lesions such as leukoplakia and erythroplakia, as well as malignant lesions including Oral Squamous Cell Carcinoma (OSCC), verrucous carcinoma, minor salivary gland carcinomas, lymphomas, melanoma, sarcomas, and metastatic tumors. The use of heterogeneous datasets improves model generalizability across different populations and imaging conditions [15].

Data Annotation
Images were annotated according to the clinical diagnosis based on source metadata. The classification scheme included premalignant and malignant lesions with subtype labels where applicable to facilitate multiclass analysis. Correct annotation is one of the important procedures in supervised learning and trusted results of a model in medical image classification tasks [16].

Data Augmentation
To address data scarcity and class imbalance, several augmentation techniques were applied:
• Rotation (±15°) for camera angle variation
• Horizontal flipping for left/right oral views
•Adjustments for brightness and contrast for lighting variations
•Random scaling for distance variation• Gaussian blur for focus variation
These transformations simulate real-world clinical conditions and im-prove model robustness and generalization [17].

Image Preprocessing
The original images were resized to 224 × 224 pixels, normalized, denoised, and contrast-improved. This pre-processing was performed to standardize the features, and improve the reliability of the subsequent image analysis steps [18].

Image Normalization
Pixel normalization scales image intensity values to a standard range:
$x' = \frac{x-\mu}{\sigma} \text{ or } x' = \frac{x}{255}$ ....(1)

where x is the original pixel value, x' is the normalized value, μ is the mean, and σ is the standard deviation. Normalization improves convergence and stability of deep learning models [36,37].

Feature Extraction
The features of the images were extracted using EfficientNet-B0 and ResNet50 transfer learning models. EfficientNet-B0 was selected due to its parameter efficiency and state-of-the-art accuracy, and ResNet50 because of its deep residual architecture and effective feature extraction capabilities. ImageNet pre-trained weights were used for both models as feature extractors. The pre-trained models were applied to the images with the last classification layer removed. These can include information about lesion texture, color distribution, shape, and structure [19].
Feature extraction in convolutional neural networks is performed using convolution:

$$S(i,j) = \sum_m \sum_n I(i+m, j+n)\, K(m,n) \qquad \ldots\ldots\ldots\ldots(2)$$

where I is the input image, K is the convolution kernel, and S is the resulting feature map. Convolution enables hierarchical extraction of spatial features from images [37].

Classification
To further improve the classification performance, an ensemble method was used that combined the feature maps extracted from EfficientNet-B0 and ResNet50, taking into account the complementary nature of these models. The k-nearest neighbors (k-NN) classifier was used to classify these combined feature vectors, with the optimal number of neighbors k being determined experimentally, and final labels determined by majority voting The combination of advanced feature extraction methods with traditional machine learning classifiers has been demonstrated to improve performance in medical image classification tasks [20].
The k-Nearest Neighbors classifier computes similarity using Euclidean distance:

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad \ldots\ldots\ldots\ldots(3)$$

where x and y are feature vectors of dimension n.

This distance metric determines the nearest neighbors for classification [39].
Majority Voting Rule (k-NN Decision)

The predicted class is assigned based on the majority label among neighbors:

$$\hat{y} = \arg\max_{c} \sum_{i \in N_k} I(y_i = c) \quad \ldots\ldots\ldots\ldots (4)$$

where N_k represents the set of k nearest samples.

Majority voting improves robustness in classification tasks [39].
Ensemble Feature Fusion
When multiple models are combined, feature fusion can be represented as:

$$F = [F_1 \mid \mid F_2] \text{ or } F = w_1F_1 + w_2F_2 \quad \ldots\ldots\ldots\ldots (5)$$

where F_1 and F_2 are feature vectors extracted from different models.

Ensemble learning enhances predictive performance by leveraging complementary information [38].

Model Training and Evaluation
The dataset was first split using stratified sampling, so that the proportion of classes was preserved in all subsets. The k-NN classifier was then trained on the resulting subset of the dataset. Various combined feature sets were tested to take advantage of complementary features. Cross-validation techniques were employed to avoid overfitting and provide reliable performance estimates. The proposed system was evaluated using common metrics such as accuracy, precision, recall (sensitivity), F1 score, confusion matrix and area under the receiver operating characteristic (ROC-AUC) curve [21].

Prediction and Output Generation
To maintain image quality, a pre-treatment is performed on the input image before features are extracted from EfficientNet-B0 and ResNet50 models. These features are then concatenated. Using k-NN classification, the input image is classified based on distance to the model's dataset in model feature space. Histological type and confidence score, proportional to the number of votes from neighboring cells, as well as relevant clinical information, are provided as model outputs following prediction of the lesion type. Use of this ensemble-based method has been shown to give more strong results [22].

Results

The proposed system was designed to automatically identify and classify oral premalignant and malignant lesions using an ensemble approach that combines EfficientNet-B0 and ResNet50 feature extractors with a k-Nearest Neighbors (k-NN) classifier. The system was evaluated on a clinically representative dataset comprising premalignant lesions (Leukoplakia, Erythroplakia) and malignant lesions including OSCC, verrucous carcinoma, minor salivary gland carcinomas, lymphomas, malignant melanoma, sarcomas, and metastatic tumors. Data augmentation and pre-processing techniques greatly helped in making the model more robust and generalizable to variations in image quality, lighting, and presentation of the anatomy [23].
The system performed equally well in binary and multi-class classification problems. The binary classifier had an accuracy of 96.7%, meaning it was highly accurate in diagnosis. The reported values for precision, recall (sensitivity) and F1-score were 96.2%, 95.8% and 96.0%, respectively. This means the high precision was achieved with low rates of false positives, the high recall or sensitivity was obtained with low rates of false negatives, and the F1-score is well balanced. Furthermore, because of the distinct morphology of OSCC, the predictive confidence scores were well above 0.95. Analysis showed that the rate of OSCC was particularly high compared to other malignant lesions for the same reason mentioned previously. Premalignant lesions like leukoplakia and erythroplakia were also detected correctly despite their subtle visual characteristics. There was a slight overlap between the premalignant lesions that have similar visual characteristics, but there was no problem in distinguishing between the malignant lesions. The ROC-AUC of 0.97 is an indication of the excellent discriminative power of the proposed model. The above results prove that the hybrid approach using the ensemble method is an accurate, reliable, and efficient solution for the automated screening and classification of oral premalignant and malignant lesions [24].

Table 1. Comparative Performance with Other Models for Oral Lesion Classification

Model	Technique Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Key Observations
SVM (Handcrafted Features)	Traditional ML	82.6	80.9	79.8	80.3	Limited ability to capture complex lesion patterns

k-NN (Handcrafted Features)	Traditional ML	85.4	83.7	82.5	83.1	Sensitive to noise and feature scaling
Random Forest	Traditional ML	87.2	86.1	85.3	85.7	Performance depends on feature quality
MobileNetV2	Lightweight CNN	90.8	89.6	88.9	89.2	Fast and computationally efficient
VGG16	Deep CNN	92.4	91.7	91.0	91.3	Good feature extraction but high parameter count
ResNet50	Deep CNN	93.6	92.8	92.1	92.4	Effective for complex lesion features
EfficientNet-B0	Efficient CNN	94.3	93.9	93.2	93.5	High accuracy with fewer parameters

As mentioned in Table 1, the performance of the models based on deep learning is significantly better compared to the traditional machine learning models for the classification of oral lesions. The best results in terms of accuracy, precision, and recall were obtained using the pro-posed ensemble model (EfficientNet-B0 + ResNet50 + k-NN) for the de-tection of premalignant and malignant oral lesions.

Discussion

The current study proposed an automated system for the detection and classification of oral premalignant and malignant lesions using an ensemble learning approach that combines EfficientNet-B0 and ResNet50 for deep feature extraction with a k-Nearest Neighbors (k-NN) classifier. The high accuracy, precision, and recall values obtained in this study clearly indicate the efficiency of the proposed approach that combines multiple deep learning models to extract complementary features of the lesions. Recent studies have clearly indicated that recent convolutional neural networks can reach expert-level performance in medical image analysis by learning complex visual patterns directly from the data [25,26]. The consideration of multiple malignant conditions, including OSCC, verrucous carcinoma, lymphomas, melanomas, sarcomas, and metastatic tumors, further emphasizes the ability of the proposed system for comprehensive clinical screening.

Data augmentation and preprocessing have been crucial in enhancing the system's robustness, especially when medical data is scarce or unbalanced. By simulating real-world variations in imaging—such as rotating, flipping, adjusting brightness, scaling, and applying Gaussian blur—performance in medical image analysis is significantly improved, as these methods increase dataset diversity without the need for additional data collection [27]. Standardized preprocessing methods, like normalization and contrast enhancement, are vital for maintaining consistent feature representation and clear lesion visualization, thus aiding in reliable classification [28].

Compared to single classifier methods, the ensemble method used in this study enhanced stability of classification process. This combination with EfficientNet-B0 built with the ability to extract parameters efficiently showed high-level features along with shallow feature maps of ResNet50 which could learn deeper hierarchy, together forming a strong fused space for classification. Ensemble methods are commonly used to reduce variance and fine-tune overall prediction accuracy through the merger of multiple feature sources [29]. Using k-Nearest Neighbors (k-NN) as the final classifier is simple, interpretable, and provides good performance when applied to high-quality feature representations [30].

The system could distinguish between the premalignant and malignant classes successfully because OSCC and other cancers have the unique morphological features which leads to better accuracy. Even though premalignant lesions are often less visually apparent, the system detected them as well, highlighting its ability to flag early disease—good news. Recent studies on oral cancer detection using image-based analytical methods have similarly reported success in distinguishing malignant lesions from precancerous conditions based on clinical images [31, 32]. The high ROC–AUC observed in this study underlines good differentiation, which is important for successful use in screening applications. In terms of the model application, transforming the model into a web app has proven its potential use in a decision support tool. These could aid early detection, preventing delay in diagnosis, and can even help healthcare professionals in settings where specialized healthcare is not available easily. AI-enhanced screening models are beginning to gain recognition as a promising adjunct for early cancer detection in both telemedicine and the clinical setting [33].

Despite these encouraging findings, there are some limitations that need to be addressed. The dataset used in this study was obtained from different open-source platforms, which may result in some variation in the imaging conditions and annotation criteria. Additionally, some of the malignant categories were represented in the dataset in relatively small numbers, which may affect the robustness of the classification. Future studies should focus on

the acquisition of larger datasets from different centers and the evaluation of more complex models such as attention or transformer models to further improve the results [34, 35].
In conclusion, the proposed ensemble-based hybrid model has shown great potential as a trustworthy and non-invasive diagnostic tool for the automatic detection and classification of oral premalignant and malignant lesions.

Conclusions

This work offers an AI-powered automated system for the detection and classification of oral premalignant and malignant lesions through an ensemble model that combines EfficientNet-B0 and ResNet50 for deep feature extraction with a k-Nearest Neighbors (k-NN) classifier. The proposed ensemble model performed well in terms of accuracy, precision, and recall for premalignant lesions and various malignant types, such as OSCC and other oral cancers. In conclusion, the ensemble model approach offers an efficient, non-invasive, and scalable solution for the early screening of oral cancer. The proposed system has great potential for use in assisting medical professionals, especially in resource-poor environments, with future applications focused on clinical validation and optimization.

Conflicts of Interest
Author states there is no conflict of interest.

Data availability statement
The study did not report any data.

Author contributions statement
Vidhi Chaudhari: Conceptualization, method development, data acquisition, data preprocessing, software development, experimental analysis, visualization, and manuscript writing.
Dr. Hitesh Patel: Supervision of research, conceptual development, validation of method, critical review, and overall project supervision.
Dr. Lokesh Gagnani: Technical development, validation of method, interpretation of results, manuscript review, and academic support.

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