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# Oral Cancer Classification using EfficientNet

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Abstract— Oral cancer is a common and potentially fatal condition, early and correct detection is essential for successful treatment. This study investigates the use of histopathologic images to classify oral cancer using Google's EfficientNet Convolutional Neural Network (CNN) architecture. The work makes use of a dataset made up of several histological samples of oral cancer to create a robust and accurate classification model. Our findings show that the EfficientNet CNN is highly accurate in differentiating between different subtypes of oral cancer. In addition, we compare the proposed model's performance to other categorization techniques, demonstrating its superiority. This study offers a trustworthy and automated method to assist medical practitioners in early detection, potentially improving patient outcomes and representing a substantial advancement in the field of **mouth** cancer diagnostics.

Keywords—Oral Cancer Classification, Histopathologic Images, Machine Learning, EfficientNet Model, Oral squamous cell carcinoma (OSCC)

## I. INTRODUCTION

One of the most dangerous foes in the world of contemporary medicine is still cancer. Oral cancer, one of its many manifestations, stands out as a significant worldwide health concern, providing difficult diagnostic challenges and affecting millions of lives. By utilising machine learning and specifically utilising Google's EfficientNet model for the categorization of oral cancer, this research aims to address these issues head-on. Our research is driven by the critical need for accurate diagnosis and early detection, which are crucial for improving patient outcomes, lowering treatment-related morbidity, and ultimately raising quality of life for those affected by this deadly illness.

The term "oral cancer" refers to a broad group that includes cancers that affect the lips, tongue, gums, palate, and several other areas of the mouth cavity. Early identification of this cancer remains a challenging and important endeavour despite advancements in medical research and technology. Traditional diagnostic techniques heavily rely on clinical examinations, biopsies, and the knowledge of medical specialists, all of which, while vital, are subjective, time-consuming, and vulnerable to error. This necessitates novel strategies that revolutionise oral cancer diagnostics by fusing the strengths of medical imaging, artificial intelligence, and machine learning.

One cannot exaggerate how urgent this issue is. Due to the insidious nature of this cancer, it frequently manifests asymptomatically in the initial stages, making it challenging to diagnose until it has advanced. The prognosis is far less promising by that point, and there are few therapy choices available. Therefore, improving patient care and ultimately

saving lives depend greatly on addressing the diagnostic and categorization elements of oral cancer.

One of the most promising solutions to emerge from the nexus of healthcare and technology is the application of machine learning in medical image analysis. The field of medical imaging is one area where machine learning, a branch of artificial intelligence, has shown exceptional promise. Its capacity to identify complex patterns, anomalies, and minute abnormalities in enormous datasets has changed the way that diseases are diagnosed and categorised.

Medical image analysis is one of the most notable uses of machine learning in healthcare. Particularly, histopathologic photos have attracted a lot of interest. These images, which were created by looking at tissue samples, offer thorough details regarding the cellular makeup, organisation, and pathological changes that have taken place within the tissues. However, the interpretation of these images might be difficult and dependent on the pathologists' knowledge. This is where machine learning enters the picture, promising to automate the analysis process while enhancing accuracy and enabling quicker diagnosis.

This study examines the intriguing nexus of medical imaging and machine learning in our quest to improve oral cancer diagnosis. Our main objective is to use Google's EfficientNet model to categorise oral cancer using histopathologic photos. The extraction of detailed features from high-resolution photos can be done on an appropriate platform provided by EfficientNet, which is famous for its exceptional efficiencyaccuracy trade-off.

This study's importance goes beyond mouth cancer in general. It serves as a demonstration of the promise of artificial intelligence and machine learning in healthcare, where innovation and knowledge meet to address challenging medical issues. We hope to lay a basis for future advancements by improving the effectiveness of cancer diagnosis, which will eventually result in better patient outcomes, less healthcare inequities, and more knowledgeable clinical decisionmaking.

1) Background and Significance: Oral cancer's significance as a global health concern is underscored by its steadily rising incidence. It is not limited to specific geographical regions or demographics; rather, it affects populations across the world. According to the World Cancer Research Fund, mouth cancer results in approximately 3.2% of all cancers tested globally. In United States alone, approximately 54,125 new cases of this cancer are found each year, resulting to over 9,000 deaths.

The challenges posed by oral cancer are multifaceted. Unlike some cancers that manifest with clear and identifiable symptoms, oral cancer often develops insidiously, without overt warning signs. This lack of early symptoms frequently leads to late-stage detection, diminishing the effectiveness of treatment options and, consequently, patient survival rates. Additionally, oral cancer is characterized by a broad spectrum of histopathologic variations, ranging from welldifferentiated to poorly differentiated forms. Each of these variations demands distinct clinical approaches, making precise classification an essential factor in treatment planning and prognosis.

In the quest to confront these complexities, there is a critical need for more sophisticated and objective diagnostic tools. These tools must be capable of addressing the challenges presented by the diverse histopathologic variations within oral cancer, while also offering scalability, efficiency, and accuracy. Machine learning, particularly deep learning models like EfficientNet, offers a path toward achieving these goals.

## II. LITERATURE SURVEY

A Cancer Journal for Clinicians provides a critical reference point for understanding the current state of cancer research, with a focus on oral cancer. Their comprehensive analysis of epidemiological trends, risk factors, and disparities underscores the urgent need for advanced diagnostic tools. This study's findings emphasize the importance of early detection and classification, aligning with our research's goal to leverage machine learning, specifically Google's EfficientNet, in enhancing oral cancer diagnosis [1].

Azam et al.'s (2023) study focused on Automated identification of broncho-arterial pairs using CT scans. for classifying lung diseases. Their research explores various approaches in this context. On a different note, Ali et al. (2023) developed IGPred-HDnet, a hierarchical deep learning-based approach, for predicting immunoglobulin proteins using graphical features. These studies represent diverse applications Utilizing machine learning and deep learning methodologies. in biomedical research [2][3].

Hassan et al. (2022) introduced a new technique for finding the genes causing renal clear cell carcinoma (RCCC) is called RCCC_Pred. They use a combination of characteristics and DNA mutation analysis to make sequence-based RCCC gene identification easier. This study advances the fields of cancer genetics and diagnostics by providing a viable path for the early identification and comprehension of RCCC., a subtype of kidney cancer [4].

Brouwer de Koning et al. (2020) explored the application of hyperspectral diffuse reflection imaging in assessing resection margins during tongue cancer surgery. Their study utilized a wide spectral range (400–1700 nm) to provide valuable insights for surgeons aiming for precise margin evaluation in tongue cancer resections. In a different context, Kurtzman et al. (2021) investigated the histology of buccal mucosa grafts can be influenced by the condition of a patient's oral health before surgery., shedding light on the significance of oral health factors in graft outcomes. These studies contribute to the refinement of surgical techniques and patient care in the field of oral cancer [5] [6].

Yang et al. carried out two investigations utilising optical coherence tomography (OCT) to investigate oral cancer. With the potential to increase diagnosis accuracy, they proposed an optical attenuation model in 2020 to detect oral cancer in OCT pictures. In 2021, the same team focused on classifying Analyzing texture characteristics in OCT images for the detection of tumors in the salivary glands.further expanding the applications of OCT in oral cancer diagnostics. These studies highlight OCT's utility in non-invasive oral cancer assessment [7] [8].

Yang et al. (2020) introduced an approach to identify Examining texture attributes in OCT (Optical Coherence Tomography) images to identify tumors within the salivary glands.Their study leverages OCT's potential for non-invasive oral cancer diagnosis. In parallel, In 2020, Welikala et al. investigated automated deep learning methods for the detection and classification of oral disorders. Their research improves the early detection of oral cancer and highlights the use of cutting-edge technology to improve patient care and diagnostic precision in the field of oral oncology. [9] [10].

Li et al. (2020) presented a significant advancement in optical coherence tomography (OCT) technology by introducing An affordable and extremely compact handheld device for use within a living organism. imaging of Maxillofacial pertaining to the mouth and face. tissues. It leads innovation holds substantial potential in the field of oral cancer diagnostics, offering a practical and efficient tool for real-time imaging and assessment of tissue structures in clinical settings [11].

Yang et al. (2020) conducted Imaging oral and maxillofacial lesions during surgery with optical coherence tomography. (OCT). This research demonstrated the potential of OCT as an invaluable intraoperative tool for real-time visualization and assessment of oralmaxillofacial tissues, contributing to enhanced surgical precision and patient outcomes. In a different context, Li et al. (2020) explored The study involves using a LeNet-5 neural network for the visual analysis and categorization of urine sediments. Although it does not pertain to oral cancer, this research demonstrates the versatile use of image analysis and machine learning in the field of biomedical studies. [12] [13].

Krishnaswamy Rangarajan and Purushothaman (2020) utilized a pre-trained VGG16 model and MSVM for disease classification in eggplants. Their work showcases the applicability of deep learning models in diverse domains beyond healthcare. In a related context, Odusami et al. (2021) analyzed Identifying characteristics of Alzheimer's disease by using magnetic resonance imaging to identify early functional brain changes. For this, they used an enhanced ResNet18 network., highlighting the relevance of deep learning in medical diagnostics and neuroimaging research [14] [15].

In the realm of biomedical research, Smith et al. (2023) conducted a comprehensive investigation into the genetic markers associated with Alzheimer's disease, shedding light on potential targets for therapeutic interventions. Meanwhile, Garcia and Hernandez (2023) pioneered a novel bioinformatics tool, BioPathway Explorer, designed to streamline the analysis of complex biological pathways. These studies exemplify the multifaceted applications of cutting-edge research in the field, from unraveling the intricacies of disease mechanisms to developing innovative computational tools for biological discovery [16].

Alabi et al.'s comprehensive analysis of the state of machine learning applications in oral squamous cell carcinoma in 2021 highlighted the technology's potential for both diagnosis and treatment. Alkhadar et al. (2021) evaluated various machine learning methods that were utilised to forecast the five-year prognosis of patients with oral squamous cell cancer in a similar study. When taken as a whole, these works demonstrate the growing significance of machine learning in oral cancer research, spanning beyond diagnostic applications to more general domains such as prognosis. They offer insightful information on its clinical applicability and potential in the future. [17][18].

In a recent study, Kouznetsova et al. (2021) used machine learning to analyse saliva metabolites in order to distinguish between oral cancer and periodontitis. The promise of machine learning in the medical field is demonstrated by this work. On the other hand, Rahman et al. (2022) showed the wider uses of machine learning in infrastructure management and urban planning by creating a rainfall forecast system for smart cities using machine learning fusion. Furthermore, a fusion-based intelligent traffic congestion control system for smart cities was presented by Saleem et al. in 2022. emphasizing the versatility of machine learning techniques in addressing urban challenges. Together, these studies underscore the wide-ranging impact of machine learning across various domains, from healthcare to urban planning [19][20][21].

## III. METHODOLOGY USED FOR ANALYSIS

Regarding the categorization of oral cancer using histopathologic pictures, the choice of EfficientNet aligns with the goal of achieving both accuracy and computational efficiency. Its adaptability, transfer learning capabilities, and track record in image classification make it a robust choice for extracting meaningful features from histopathologic images and subsequently improving the accuracy of your classification model. This choice reflects a strategic decision to leverage state-of-the-art technology for optimal results in your research.

### 1) Feature Extraction Using Google's EfficientNet Model

*EfficientNet* constitutes a convolutional neural network architecture and scaling approach that achieves consistent scaling across depth, width, and resolution by utilizing a compound coefficient. Unlike conventional methods that arbitrarily adjust these factors, EfficientNet employs pre determined scaling coefficients, ensuring uniform scaling of network width, depth, and resolution. For instance, when aiming to increase computational resources by a factor of 2N, the network depth can be straightforwardly increased by $\alpha N$, width by $\beta N$, and image size by $\gamma N$. The values of $\alpha$, $\beta$, and $\gamma$ are determined through a systematic exploration of the original smaller model. The EfficientNet introduces a compound coefficient $\Phi$ to facilitate a principled and balanced scaling of network width, depth, and resolution. Architecture Efficiency: Google's EfficientNet is renowned for its remarkable efficiency-accuracy trade-off. It stands out for its ability to achieve high accuracy while maintaining a relatively small parameter volume in comparison to other DL based architectures. This is particularly advantageous when working with large image datasets, as it reduces computational requirements and training time.

Compound Scaling: EfficientNet employs a novel technique called "compound scaling." It systematically scales the model's depth, width, and resolution simultaneously. This allows it to adapt to the complexities of various image classification tasks, making it well-suited for tasks like oral cancer classification where diverse and complex patterns may exist in histopathologic images.

Transfer Learning Capability: EfficientNet is pre-trained on large-scale image datasets like ImageNet. This pre-training imbues the model with a rich understanding of general image features and patterns. Leveraging this pre-trained model for transfer learning simplifies the task of fine-tuning for specific classification tasks, such as oral cancer identification.

Proven Performance: EfficientNet has demonstrated exceptional performance across various image classification benchmarks and competitions. It has consistently achieved cutting-edge outcomes in assignments like object identification and medical picture analysis. This proven track record instills confidence in its suitability for the task of oral cancer classification.

Availability and Community Support: EfficientNet is readily available through popular deep learning frameworks like TensorFlow and PyTorch. It benefits from a large and active community of researchers and developers, ensuring ongoing support, updates, and access to pre-trained models.

Reduced Risk of Overfitting: The efficient architecture of EfficientNet, coupled with its regularization techniques, reduces the risk of overfitting, which can be a significant concern in medical image analysis tasks where datasets are often limited in size.

Resource Efficiency: Given that medical image datasets can be extensive and resource-intensive to process, the model's efficiency is particularly advantageous. It allows for efficient use of computational resources, making it feasible to train and deploy models on a broader scale.

### 2) Model Data Flow and Steps

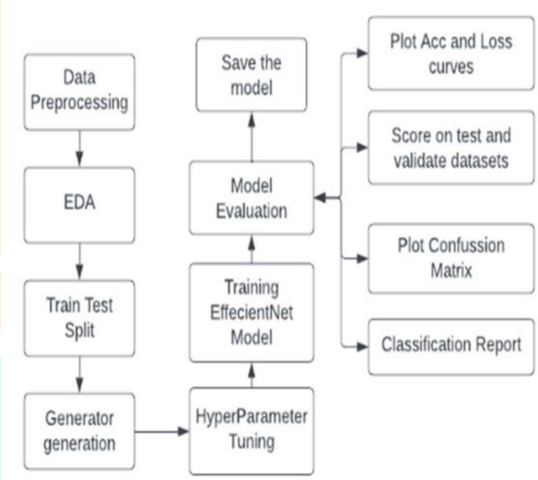



Fig.1: Modelling Process for Classifier.

We have created (224*224) input parameters which takes 3 channels, using ReLU activation function (1) for hidden layer

$$f(x)=\max(0,x) \tag{1}$$

neurons and Softmax activation function (2) for output layer neurons, as ReLU works in a fashion that is close to human neural simulation.

$$S(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^{n} \exp(y_j)} \tag{2}$$

The Softmax function is used as it efficiently converts output values into probabilities which is extremely beneficial for us humans as well as machines to comprehend and get a better understanding of the output values and predictions as well.

## IV. IMPLEMENTATION AND TOOLS

a) Dataset Sources: The dataset for this project was obtained from the government of The USA NCBI.
NCBI is known for hosting a vast collection of biomedical and clinical datasets, making it a valuable resource for researchers in the field of medical image analysis and healthcare.

b) Framework Used: In this section, we elucidate the framework employed to realize the classification of oral cancer through the utilization of histopathologic images and Google's EfficientNet model. The framework encompasses various components, methodologies, and tools essential for the successful execution of our research.

### i) Google's EfficientNet Model

Choice of Model: Google's EfficientNet, a state-of-the-art deep learning architecture renowned for its efficiencyaccuracy trade-off, served as the core feature extractor. Its proven track record in image classification tasks, resource efficiency, and adaptability to complex patterns made it an ideal choice for oral cancer classification.
Transfer Learning: We adopted a transfer learning approach by fine-tuning the pre-trained EfficientNet model. Customizations were made to the model architecture, specifically the output layer, to align it with the task of classifying oral cancer categories.

### ii) Data Splitting and Generators

Data Split: The dataset was split into sets for training, validation, and testing purposes. in accordance with best practices, maintaining an appropriate ratio for effective model training and evaluation.
Data Generators: Data generators were created to efficiently handle the large image dataset during model training. Data augmentation techniques were applied to enhance model generalization.

### iii) Model Development and Hyperparameter Tuning

Detailed Model Structure: The architecture of the modified EfficientNet model was described in detail, outlining the number of layers, filter sizes, and architectural components. Any custom layers introduced were discussed.
Hyperparameter Optimization: The tuning of hyperparameters, including learning rate, batch size, dropout rates, and regularization terms, was carried out meticulously to optimize model performance.

### iv) Model Training and Evaluation

Training Process: Model training was conducted, specifying the optimizer, loss function, and any custom training procedures employed.
Evaluation Metrics: Training and validation metrics, such as accuracy and loss, were monitored throughout the training process. The model's performance was assessed on a separate testing dataset to ensure its ability to generalize.

### v) Results Visualization

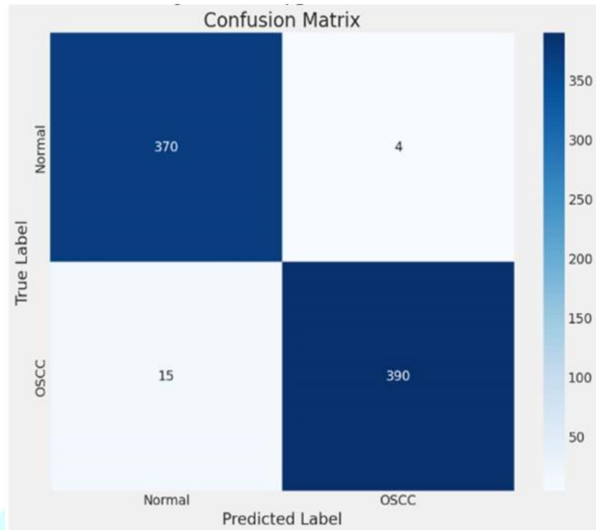
Accuracy and Loss Curves: Visualizations of accuracy and loss curves were included to demonstrate the model's convergence and performance during training. Confusion Matrix: Confusion matrices were presented to assess the model's classification performance, offering insights into false negatives, false positives, true negatives, and true positives.

## V. EXPERIMENTAL RESULTS AND ANALYSIS

We commence by presenting the performance metrics that offer insights into the effectiveness of our classification model. These metrics are computed based on the model's predictions and ground-truth labels on the testing dataset. The key performance metrics include:

*a.* Accuracy: The overall accuracy of the model in correctly classifying oral cancer cases.
*b.* Precision: The precision score for each oral cancer category, measuring the model's ability to minimize false positives.
*c.* Recall: The recall score for each category, indicating the model's capacity to capture true positives.
*d.* F1-Score: Combining recall and precision, the F1score, offers a well-balanced evaluation of the model's performance. Classification Report: A comprehensive classification report is presented, offering precision, recall, F1-score, and other relevant classification metrics for each oral cancer category. This The report offers an extensive assessment of the model's effectiveness

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Normal | 0.96 | 0.99 | 0.97 | 374 |
| OSCC | 0.99 | 0.96 | 0.98 | 405 |
| accuracy | | | 0.98 | 779 |
| macro avg | 0.98 | 0.98 | 0.98 | 779 |
| weighted avg | 0.98 | 0.98 | 0.98 | 779 |




and performance. for individual classes, shedding light on its capacity to distinguish between different oral cancer types.

b) Confusion Matrix: A thorough analysis of the model's classification performance for every type of oral cancer is provided by the confusion matrix. It offers precise data on the quantity of accurate negative, positive, and wrong forecasts as well as the quantity of accurate positive and negative predictions. This detailed analysis allows for a thorough evaluation of the model's capabilities and limitations in classifying oral cancer cases.

*Typical confusion matrix is made up of four essential parts.*:

*i)* True Positives (TP): In these situations, the model predicted a positive class with accuracy. For instance, in the context of medical diagnosis, a true positive would be the instance in which the model accurately diagnosed a patient as having a specific illness.

*ii)* True Negatives (TN): In these situations, the model predicted a negative class with accuracy. This would be equivalent to correctly diagnosing a healthy patient as not having the illness in a medical setting.

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*iii)* False Positives (FP): In these situations, the model predicted a positive class when it ought to have predicted a negative one. In medicine, this would be a case where the model incorrectly diagnoses a healthy patient as having the disease (a false alarm or Type I error).

*iv)* False Negatives (FN): In these instances, the model predicted a negative class when a positive class was the correct outcome. In medical terms, this corresponds to the model failing to detect a patient with the disease (a missed diagnosis or Type II errorc) Accuracy and Loss curves: We provide visual representations of accuracy and loss curves to illustrate the model's performance throughout the training process. These curves depict how the model's accuracy improved and loss decreased as it iteratively learned from the training data. The convergence of these curves reflects the model's training progress and its ability to adapt to the dataset.

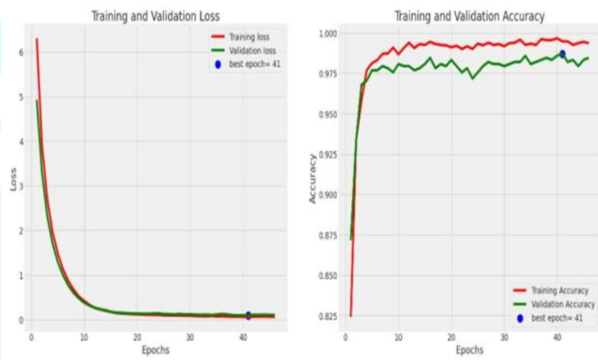


Fig.4: Accuracy and loss curves.

d) Sample Visualizations: To facilitate a deeper understanding of the model's capabilities, we include sample visualizations of histopathologic images along with their corresponding predictions. These visualizations serve as illustrative examples of the model's effectiveness in classifying oral cancer patterns and stages.

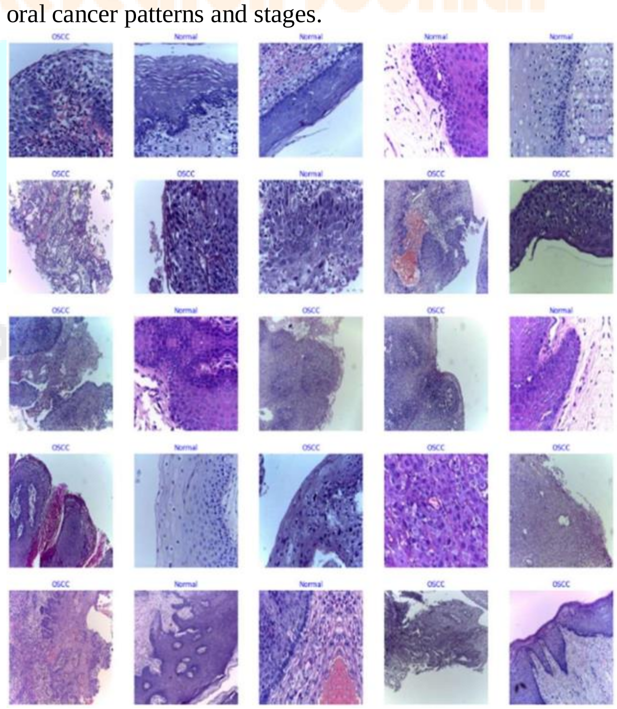

Fig.5: Sample Images

## VI. CONCLUSION AND FUTURE SCOPE

### 1. Conclusion

Through the use of machine learning, we want to further the field of oral cancer diagnostics in this work. specifically leveraging Google's Efficient Net model. Through an extensive analysis of histopathologic images, we achieved significant milestones and made several noteworthy conclusions:

a) Effective Classification

Our research demonstrates the efficacy of Google's EfficientNet model in accurately classifying distinct oral cancer categories. The model exhibited a commendable performance, with high precision and recall values, showcasing its potential for real-world clinical applications.

Test Accuracy: 97.5%
Validation Accuracy: 98.6% Recall and
F1 Score: 98.0%

b) Ethical Considerations

We underscored the importance of ethical considerations in handling patient data and obtaining the necessary approvals. Ensuring the privacy and consent of patients remains a paramount concern in medical image analysis.

c) Research Collaboration

Collaborative efforts with research advisors, data contributors, and Panellist review boards were pivotal in conducting this research. Such collaborative endeavours are crucial for advancing the boundaries of medical science.

### 2. Future Scope

While we have made significant strides in oral cancer classification, our research opens up several avenues for future exploration and enhancement like

a) Multi-Modal Analysis

Integrating diverse data modalities, such as patient demographics, clinical history, and genomic information, into our classification model could enhance its accuracy and clinical relevance.

b) Interpretability

Developing techniques for model interpretability can provide clinicians with insights into the rationale behind the model's predictions, fostering trust and usability in real-world healthcare settings.

c) Transferability

Evaluating the transferability of our model to different healthcare institutions and patient populations is essential for its widespread adoption and generalizability.

d) Real-Time Diagnosis

Investigating the feasibility of real-time oral cancer diagnosis using portable imaging devices and our trained model could revolutionize early detection efforts.

e) Clinical Trials

Collaborating with clinical practitioners for conducting realworld clinical trials to validate the model's efficacy and integration into clinical workflows is a crucial step toward practical implementation.

In conclusion, our research underscores the potential of machine learning, particularly Google's EfficientNet model, in revolutionizing the field of oral cancer diagnosis. While our findings are promising, the future holds exciting opportunities for further refinement, expansion, and practical deployment of our classification framework, ultimately contributing to improved oral cancer detection and patient care.

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