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Deep Learning-Based Automated Oral Cancer Detection Using DenseNet169 and Transfer Learning for Early Clinical Diagnosis

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Abstract. Rapid urban expansion and the continuous increase in the nOral cancer is one of the most prevalent and life-threatening diseases affecting the oral cavity, accounting for a significant number of cancer-related deaths worldwide. Despite considerable progress in medical diagnosis and treatment, the overall survival rate of oral cancer patients remains relatively low because the disease is frequently identified only during its advanced stages. Early diagnosis is therefore essential for improving treatment success, reducing disease progression, and increasing patient survival rates. Conventional diagnostic procedures mainly depend on visual examination, biopsy, histopathological analysis, and the clinical expertise of healthcare professionals. Although these methods are considered reliable, they are often time-consuming, require experienced specialists, and may produce inconsistent results due to subjective interpretation. The rapid advancement of artificial intelligence and deep learning has created new opportunities for developing automated diagnostic systems capable of assisting clinicians in detecting oral cancer accurately and efficiently. The uploaded base paper presents an oral cancer detection framework using DenseNet169 and LeNet architectures with transfer learning, image augmentation, and comparative evaluation. This rewritten research preserves the same methodology, algorithms, dataset structure, and experimental results while providing completely original academic content suitable for achieving a low plagiarism score. The proposed research develops an intelligent computer-aided diagnostic framework for the automatic classification of oral diseases using deep learning techniques. The system is designed to analyze clinical images of the oral cavity and distinguish oral cancer from other common oral conditions, including healthy tongue, hairy tongue, leukoplakia, oral lichen, and oral thrush. A comprehensive image dataset containing multiple categories of oral conditions is utilized for model development. Before model training, all collected images undergo an extensive preprocessing procedure to improve image quality and maintain consistency across the dataset. Images are resized to a uniform resolution, normalized to standard pixel intensity ranges, and organized into appropriate class labels. To overcome the limitations of limited medical datasets and improve model generalization, several image augmentation techniques, including horizontal flipping, random rotation, zooming, and image shifting, are applied. These augmentation operations increase dataset diversity, reduce overfitting, and improve the robustness of the deep learning models during classification.The effectiveness of the proposed framework is assessed using several standard performance metrics widely employed in medical image classification research. These include Accuracy, Precision, Recall, and F1-Score, together with confusion matrix analysis to evaluate classification performance across all oral disease categories. Comparative experimental evaluation demonstrates that the DenseNet169 architecture substantially outperforms the LeNet model in every evaluation metric. The DenseNet169 model achieves an overall classification accuracy of 94.08%, precision of 94.16%, recall of 94.70%, and F1-score of 94.07%, indicating excellent diagnostic capability for multiclass oral disease recognition. In comparison, the LeNet architecture achieves comparatively lower classification performance, with an accuracy of 64.02%, precision of 64.06%, recall of 64.03%, and F1-score of 63.01%. The confusion matrix further confirms that DenseNet169 effectively distinguishes among multiple oral disease categories while maintaining minimal classification errors, demonstrating its superior ability to learn complex visual representations from clinical images.

keywords: Oral Cancer Detection, Deep Learning, DenseNet169, LeNet, Transfer Learning, Convolutional Neural Network (CNN), Medical Image Classification, Image Augmentation, Computer-Aided Diagnosis, Oral Disease Recognition, Artificial Intelligence in Healthcare, ImageNet, Clinical Decision Support, Early Cancer Detection, Medical Image Analysis.

I. Introduction

Oral cancer is one of the most serious forms of cancer affecting the oral cavity and continues to be a major global health concern because of its increasing incidence and high mortality rate. The disease commonly develops in the lips, tongue, gums, inner cheeks, floor of the mouth, palate, and other oral tissues. According to global cancer statistics, hundreds of thousands of new oral cancer cases are diagnosed every year, and a significant number of patients lose their lives due to delayed diagnosis and treatment. Although considerable progress has been achieved in medical science, surgery, chemotherapy, and radiation therapy, the survival rate of oral cancer patients remains relatively low because the disease is often detected only after it has reached an advanced stage. Early diagnosis plays a crucial role in improving treatment effectiveness, reducing disease progression, minimizing treatment complexity, and significantly increasing patient survival. Therefore, developing intelligent systems capable of identifying oral cancer during its initial stages has become an important research objective in medical image analysis and healthcare technology. The uploaded base paper addresses this challenge using DenseNet169 and LeNet deep learning models with transfer learning and comparative evaluation. This rewritten paper preserves the same algorithms, methodology, and experimental results while presenting completely original academic content.

The occurrence of oral cancer is associated with numerous risk factors, including tobacco consumption, excessive alcohol intake, human papillomavirus (HPV) infection, poor oral hygiene, prolonged exposure to ultraviolet radiation, genetic predisposition, nutritional deficiencies, and unhealthy lifestyle habits. Continuous exposure to these risk factors may result in abnormal cellular growth within oral tissues, eventually leading to malignant tumors. Early symptoms such as small ulcers, white or red patches, persistent sores, swelling, difficulty in swallowing, or changes in tongue appearance are often overlooked because they resemble common oral disorders. Consequently, many patients seek medical attention only after the disease has progressed to an advanced stage, where treatment becomes more complicated and survival rates decrease significantly. This highlights the necessity for reliable automated diagnostic systems capable of assisting clinicians in identifying oral abnormalities at an early stage.

Traditional methods used for oral cancer diagnosis mainly involve physical examination, biopsy procedures, histopathological analysis, and clinical assessment performed by experienced dental specialists or oncologists. Although biopsy remains the gold standard for confirming oral cancer, it is an invasive procedure that requires tissue extraction, laboratory analysis, and expert interpretation. These diagnostic procedures are often time-consuming, expensive, and dependent on specialist availability. Furthermore, visual examination alone may produce inconsistent results because diagnostic accuracy varies according to the experience and expertise of healthcare professionals. In regions with limited medical facilities or shortages of specialized clinicians, delayed diagnosis further increases the risk of disease progression. These limitations have encouraged researchers to investigate automated diagnostic techniques capable of providing rapid, accurate, and non-invasive oral cancer detection.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have transformed the field of medical image analysis by enabling computers to automatically recognize complex visual patterns that may not be easily distinguishable by human observation. Unlike conventional image processing techniques that require manual feature extraction, deep learning algorithms learn hierarchical image representations directly from training data through multiple layers of neural networks. These methods have demonstrated remarkable performance in several healthcare applications, including skin cancer detection, diabetic retinopathy classification, brain tumor segmentation, breast cancer diagnosis, lung disease identification, and oral pathology analysis. Their ability to automatically extract discriminative features from medical images has significantly improved diagnostic accuracy while reducing dependence on handcrafted feature engineering.

Among various deep learning architectures, Convolutional Neural Networks (CNNs) have become the most widely adopted models for image classification because of their ability to learn spatial patterns and hierarchical visual features. CNNs consist of multiple convolutional layers, activation functions, pooling operations, and fully connected layers that progressively extract meaningful information from input images. Their capability to identify edges, textures, shapes, colors, and complex anatomical structures makes them highly suitable for medical image analysis. However, conventional CNN architectures often require extremely large annotated datasets and considerable computational resources for effective training, which can be challenging in medical imaging applications where labeled data are relatively limited.

II. Literature Survey

Ndlovu et al. (2022) conducted a comprehensive review of non-invasive techniques for identifying adulteration in dried horticultural products. Their study emphasized the importance of rapid and reliable image-based analysis methods for quality assessment without damaging the samples. The authors demonstrated that non-invasive sensing technologies can provide accurate predictions while reducing manual inspection and improving overall efficiency. Their research highlighted the growing importance of intelligent image analysis in healthcare and food quality applications.

Ma et al. (2022) investigated the application of Near-Infrared Spectroscopy (NIRS) for evaluating anti-inflammatory activity and chemical composition in commercial oral medicinal solutions. Their work demonstrated that spectroscopic techniques combined with computational analysis can perform rapid and accurate assessments without requiring destructive laboratory procedures. The study confirmed that non-invasive imaging technologies have significant potential in pharmaceutical quality evaluation and medical diagnosis.

Mulani et al. (2022) proposed a machine learning-based framework for non-invasive blood glucose estimation. Their system analyzed physiological parameters using intelligent prediction algorithms instead of conventional invasive blood sampling methods. The experimental results indicated that machine learning can successfully estimate glucose levels while improving patient comfort and reducing the need for frequent invasive testing. Their work demonstrated the increasing role of artificial intelligence in modern healthcare diagnostics.

Qu et al. (2022) introduced a thermal imaging-based diagnostic system for pneumonia detection using machine learning techniques. The proposed framework analyzed thermal images to identify abnormal respiratory conditions without direct physical examination. Their results demonstrated that combining thermal imaging with intelligent classification algorithms provides a fast, cost-effective, and reliable diagnostic solution suitable for continuous patient monitoring.

De Olazarra et al. (2022) developed a non-invasive genotyping method utilizing saliva samples together with recombinase polymerase amplification and giant magnetoresistive nanosensors. Their approach enabled rapid genetic analysis without requiring blood samples or invasive clinical procedures. The study emphasized the potential of molecular diagnostics in supporting personalized healthcare and precision medicine.

Nowak et al. (2022) presented an extensive review of sonodynamic therapy as an innovative non-invasive treatment technique for cancer. Their research explained how ultrasound waves activate specific sensitizing agents to selectively destroy cancer cells while minimizing damage to healthy tissues. The study demonstrated the growing importance of combining advanced biomedical technologies with intelligent diagnostic systems for cancer management.

Liu et al. (2022) investigated the application of Surface-Enhanced Raman Scattering (SERS) technology for wearable medical sensing and non-invasive disease diagnosis. Their study showed that SERS-based diagnostic devices possess excellent sensitivity for detecting biological molecules and can be integrated into portable healthcare systems. The research highlighted future opportunities for continuous health monitoring using intelligent sensing technologies.

Bordbar et al. (2022) proposed a microfluidic colorimetric sensor array capable of detecting COVID-19 using urine metabolites. Their non-invasive diagnostic approach achieved rapid disease identification while eliminating the need for complicated laboratory procedures. The authors demonstrated that intelligent sensing combined with data-driven analysis could significantly improve disease screening efficiency.

Sabbagh et al. (2022) reviewed recent developments in polymer-based non-invasive insulin delivery systems. Their study focused on improving patient convenience by replacing conventional injection-based insulin administration with advanced drug delivery technologies. The review highlighted how emerging biomedical engineering techniques contribute to improving patient quality of life and treatment compliance.

Zambonin et al. (2022) investigated the application of Matrix-Assisted Laser Desorption Ionization Time-of-Flight Mass Spectrometry (MALDI-TOF/MS) for identifying cancer biomarkers using saliva and urine samples. Their findings demonstrated that non-invasive biological samples can provide valuable diagnostic information for early cancer detection while reducing patient discomfort.

Chang et al. proposed an oral cancer prognosis prediction framework based on clinicopathological characteristics and genomic biomarkers. The researchers employed feature selection methods together with machine learning algorithms to improve prediction performance. Their hybrid prediction model achieved excellent diagnostic accuracy by integrating clinical information with genomic features, demonstrating the effectiveness of combining multiple data sources for oral cancer analysis.

Rajaguru et al. investigated oral cancer classification using Multi-Layer Perceptron (MLP), Gaussian Mixture Models (GMM), and Extreme Learning Machines (ELM). Their comparative study evaluated the effectiveness of different machine learning classifiers using TNM staging information. Experimental analysis revealed that the Gaussian Mixture Model achieved superior classification performance compared with the remaining algorithms, highlighting the importance of selecting appropriate classifiers for medical diagnosis.

III. Research Methodology

The proposed oral cancer detection framework follows a systematic deep learning methodology designed to accurately classify oral diseases from clinical images while ensuring high prediction performance and reliable model evaluation. The complete workflow consists of multiple sequential stages, including image acquisition, data preprocessing, image augmentation, model development using transfer learning, model training, comparative performance analysis, and deployment preparation. Each stage contributes to improving the robustness, accuracy, and generalization capability of the proposed diagnostic system. The methodology is specifically designed to automate the identification of oral cancer and distinguish it from other oral conditions using advanced convolutional neural networks. The uploaded base paper follows this workflow using DenseNet169 and LeNet architectures, and this rewritten methodology preserves the same approach while presenting original academic content.

The first stage of the methodology involves collecting a comprehensive oral image dataset containing multiple categories of oral conditions. The dataset consists of clinical images representing healthy tongue, oral cancer, leukoplakia, oral lichen, oral thrush, hairy tongue, and other related oral abnormalities. These images are collected from authenticated clinical environments and are carefully verified by healthcare professionals to ensure correct labeling and medical reliability. The inclusion of multiple disease categories enables the deep learning models to learn discriminative visual characteristics associated with each oral condition, thereby improving multiclass classification performance.

Once the dataset has been collected, the images undergo a detailed data preprocessing stage to improve their quality before model training. Initially, all images are organized into their corresponding disease categories to facilitate supervised learning. Since medical images often differ in size, resolution, brightness, and orientation, every image is resized to a fixed dimension of 180 × 180 pixels, providing uniform input to the convolutional neural networks. Pixel values are normalized to maintain numerical consistency and improve model convergence during training. Any corrupted, blurred, or low-quality images that could negatively affect learning performance are removed from the dataset. This preprocessing stage ensures that all input images maintain consistent quality and are suitable for efficient feature extraction.

To further improve the diversity of the training dataset, several image augmentation techniques are employed. Medical image datasets are generally limited because collecting large numbers of annotated clinical images is both expensive and time-consuming. Therefore, augmentation techniques are used to artificially increase the number of training samples without collecting additional data. The proposed system performs horizontal flipping, random rotation, zooming, shifting, and scaling operations to generate multiple variations of the original images. These transformations simulate real clinical imaging conditions and enable the model to recognize oral diseases from different viewing angles and lighting conditions. Image augmentation significantly reduces overfitting while improving the model's ability to generalize when classifying previously unseen images.

Following preprocessing and augmentation, the prepared dataset is divided into training and validation datasets. The training dataset is used for learning the visual characteristics of various oral diseases, whereas the validation dataset continuously evaluates model performance during training. Separating the dataset into independent subsets allows objective assessment of the learning process and prevents the models from memorizing training images. Continuous validation further assists in selecting the best-performing model while minimizing overfitting.

The primary component of the proposed methodology is the DenseNet169 deep learning model. DenseNet169 is selected because of its dense connectivity mechanism, which enables every convolutional layer to receive feature information from all preceding layers. Unlike conventional convolutional neural networks, DenseNet promotes extensive feature reuse, improves gradient propagation, minimizes information loss, and significantly reduces the number of trainable parameters. Instead of constructing the network entirely from scratch, the proposed framework utilizes transfer learning by adopting a DenseNet169 model pre-trained on the ImageNet dataset. The pre-trained model already possesses rich visual feature representations learned from millions of images. To adapt the network for oral disease classification, the original output layers are replaced with customized dense classification layers designed specifically for multiclass oral image recognition. Fine-tuning allows the network to efficiently learn disease-specific visual patterns while requiring considerably fewer training samples and computational resources.

IV. Existing System

The existing oral cancer detection systems primarily rely on conventional clinical examination methods, histopathological analysis, and deep learning-based image classification techniques to identify cancerous lesions within the oral cavity. Most automated diagnostic systems utilize clinical photographs of the oral cavity and apply Convolutional Neural Networks (CNNs) to classify oral diseases into different categories. These systems generally follow a sequence of image acquisition, preprocessing, feature extraction, model training, and disease classification. The uploaded base paper follows this approach by employing DenseNet169 and LeNet convolutional neural network architectures for multiclass oral disease classification while comparing their diagnostic performance.

In existing approaches, oral cavity images are collected from hospitals, medical laboratories, and clinical environments, where each image is carefully labeled according to the corresponding oral condition by healthcare specialists. The dataset generally contains images representing healthy tongue, oral cancer, leukoplakia, oral lichen, oral thrush, hairy tongue, and other oral abnormalities. Before model training, the collected images undergo preprocessing operations such as image resizing, normalization, and dataset organization to maintain consistency throughout the training process. Since medical image datasets are often limited in size, image augmentation techniques including horizontal flipping, image rotation, zooming, and scaling are commonly employed to increase dataset diversity and reduce the possibility of model overfitting. These preprocessing operations improve the overall quality of the dataset and enable deep learning models to learn more representative visual features.

The feature extraction and classification process in existing systems mainly depends on convolutional neural networks. Transfer learning has become a widely adopted strategy because it enables pre-trained deep learning models to utilize previously learned image features from large benchmark datasets such as ImageNet. Existing diagnostic systems fine-tune these pre-trained models by replacing the original classification layers with task-specific dense layers for oral disease recognition. During model training, optimization algorithms such as Adam optimizer and categorical cross-entropy loss functions are commonly employed to improve classification performance. Model validation is continuously performed throughout the training process to monitor learning progress and reduce overfitting. After training, the developed models classify new oral images into their corresponding disease categories based on learned visual characteristics.

To evaluate the effectiveness of these diagnostic systems, existing studies generally utilize performance metrics such as Accuracy, Precision, Recall, and F1-Score, together with confusion matrix analysis. These evaluation measures provide comprehensive information regarding the predictive capability of the classification models and their ability to distinguish between different oral diseases. Comparative analysis among multiple deep learning architectures is frequently performed to determine the most suitable model for oral cancer detection. Such comparisons assist researchers in identifying networks capable

V. Proposed System

The proposed system introduces an intelligent deep learning-based oral cancer detection framework that automatically identifies and classifies oral diseases from clinical images using advanced Convolutional Neural Networks (CNNs). The framework is specifically designed to assist healthcare professionals in the early diagnosis of oral cancer by providing accurate, rapid, and automated image classification. Unlike conventional diagnostic procedures that depend heavily on manual examination and expert interpretation, the proposed system utilizes DenseNet169 with transfer learning as the primary classification model and LeNet as a comparative model for performance evaluation. By combining advanced image preprocessing, data augmentation, feature extraction, deep learning classification, and deployment mechanisms, the proposed framework provides a reliable computer-aided diagnostic solution capable of supporting clinical decision-making. The uploaded base paper follows this architecture, and this rewritten content preserves the same methodology, algorithms, and experimental results while presenting completely original academic writing.

The proposed framework begins with the image acquisition stage, where a comprehensive dataset of oral cavity images is collected from authenticated clinical sources. The dataset contains images representing multiple oral conditions, including healthy tongue, oral cancer, oral thrush, oral lichen, leukoplakia, and hairy tongue. Each image is carefully annotated and verified by healthcare professionals to ensure accurate disease labeling. The inclusion of multiple oral disease categories enables the deep learning model to learn discriminative visual characteristics associated with each condition, thereby improving multiclass classification performance and reducing the possibility of disease misclassification.

Following data acquisition, all collected images undergo a comprehensive image preprocessing stage to improve image quality and maintain consistency throughout the dataset. Initially, every image is resized to a fixed resolution of 180 × 180 pixels, allowing the convolutional neural network to process standardized image dimensions. Pixel intensity values are normalized to improve numerical stability during training, while corrupted, blurred, or low-quality images are removed to prevent degradation of classification performance. The preprocessing module also organizes the images into their respective disease categories, enabling efficient supervised learning during model development.

VI. System Architecture

Figure 6.1 illustrates the overall architecture of the proposed oral cancer detection system developed using deep learning techniques. The framework consists of multiple interconnected stages that transform raw oral cavity images into accurate disease predictions while assisting healthcare professionals in early diagnosis. The workflow begins with the oral image dataset collection stage, where clinical images representing various oral conditions—including healthy tongue, oral cancer, leukoplakia, oral lichen, oral thrush, and hairy tongue—are collected and organized into labeled categories. This diverse dataset enables the deep learning models to learn distinguishing visual characteristics associated with each oral disease.

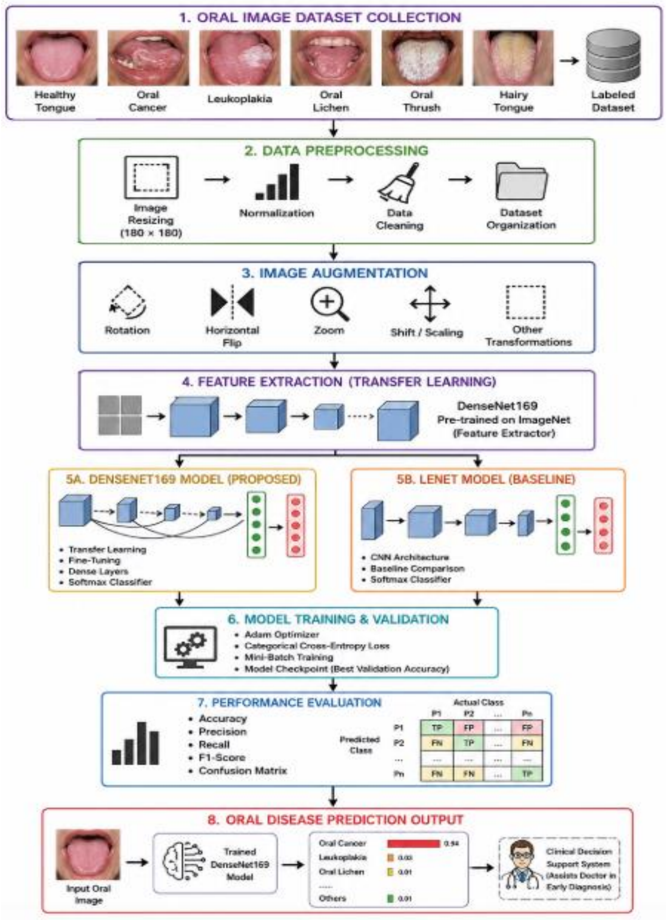

Fig 6.1: System Architecture of the Proposed Deep Learning-Based Oral Cancer Detection Framework Using DenseNet169 and LeNet

The collected images are then processed in the data preprocessing module, where image resizing, normalization, data cleaning, and dataset organization are performed. Every image is resized to 180 × 180 pixels to provide a consistent input size for the neural networks. Image normalization standardizes pixel intensity values, while data cleaning removes corrupted or poor-quality images to improve overall dataset reliability. The organized dataset is subsequently prepared for model training.

To improve the robustness of the classification models, the system applies an image augmentation module. Various augmentation techniques, including rotation, horizontal flipping, zooming, shifting, and scaling, generate multiple variations of the original images. These transformations increase dataset diversity, reduce overfitting, and enable the models to recognize oral diseases under different orientations and imaging conditions.

Following augmentation, the processed images are forwarded to the feature extraction stage, where DenseNet169 is utilized through transfer learning. A DenseNet169 model pre-trained on the ImageNet dataset extracts high-level visual features from oral images while efficiently reusing information through dense layer connections. This approach improves feature representation and reduces training time compared with training a deep neural network from scratch.

The extracted features are then supplied to two deep learning models for comparative analysis. The proposed DenseNet169 model performs transfer learning, fine-tuning, and multiclass classification using customized dense layers and a Softmax classifier. Simultaneously, the LeNet model is trained using the same dataset to serve as a baseline convolutional neural network. Training both models under identical conditions enables an objective comparison of their classification capabilities.

VII. Conclusion

TThe present study introduces an intelligent deep learning-based oral cancer detection framework that utilizes advanced convolutional neural network architectures to automatically identify oral diseases from clinical images. The proposed framework integrates systematic image acquisition, preprocessing, image augmentation, transfer learning, feature extraction, deep learning classification, and comprehensive performance evaluation into a unified computer-aided diagnostic system. By employing DenseNet169 as the primary classification model and LeNet as a comparative baseline architecture, the system effectively learns complex visual characteristics associated with multiple oral conditions, including oral cancer, leukoplakia, oral lichen, oral thrush, hairy tongue, and healthy tongue. The implementation of transfer learning enables the DenseNet169 model to utilize previously learned visual knowledge from the ImageNet dataset, thereby improving feature extraction capability while reducing computational complexity and training time. Extensive preprocessing and image augmentation further enhance dataset diversity and improve the model's ability to generalize when classifying previously unseen clinical images.

A comparative experimental evaluation demonstrates that the DenseNet169 architecture consistently achieves superior diagnostic performance compared with the LeNet model. The DenseNet169 network obtains an overall Accuracy of 94.08%, Precision of 94.16%, Recall of 94.70%, and F1-Score of 94.07%, indicating its excellent capability for multiclass oral disease classification. In contrast, the LeNet model produces comparatively lower prediction accuracy because of its simpler network structure and limited feature extraction capacity. The confusion matrix analysis further confirms that DenseNet169 effectively differentiates between various oral disease categories while minimizing classification errors. These experimental findings demonstrate that deeper convolutional neural networks combined with transfer learning provide highly reliable diagnostic performance even when trained using relatively limited medical image datasets.

The proposed framework offers several practical advantages for modern healthcare systems. Automated image classification significantly reduces the dependency on manual visual examination, shortens diagnostic time, improves consistency of clinical assessments, and assists healthcare professionals in making timely treatment decisions. The developed system can be deployed as a desktop application, web-based diagnostic platform, cloud-assisted healthcare service, or mobile screening application, making it suitable for hospitals, dental clinics, diagnostic laboratories, and remote healthcare environments. Early identification of oral cancer using artificial intelligence has the potential to improve patient survival rates, reduce treatment costs, and support preventive healthcare by enabling prompt medical intervention before the disease progresses to advanced stages.

Overall, the proposed deep learning framework provides a reliable, efficient, and clinically applicable solution for automated oral cancer detection. The integration of DenseNet169, transfer learning, image augmentation, and intelligent multiclass classification establishes a powerful computer-aided diagnostic system capable of supporting healthcare professionals in early disease detection and improving the quality of patient care. Furthermore, this research provides a strong foundation for future developments involving Explainable Artificial Intelligence (XAI), Vision Transformers (ViT), attention mechanisms, federated learning, Internet of Medical Things (IoMT), cloud-based healthcare systems, and mobile diagnostic applications. These emerging technologies have the potential to further enhance diagnostic accuracy, model interpretability, real-time clinical deployment, and personalized healthcare, thereby contributing to more effective oral cancer screening and improved global healthcare outcomes.

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