Stage-wise Classification of Oral Diseases using DenseNet201 Deep Learning Model

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***Abstract*—In order to improve patient outcomes and avoid serious dental consequences, early diagnosis of oral disorders is essential. A deep learning-based system for the automated categorization of two important oral diseases dental cavities (enamel caries) and gum disease (periodontitis) is presented in this paper. Using DenseNet201 as the backbone model, the system classifies disease stages into early, moderate, and advanced categories. Balanced dataset and preprocessing techniques were applied to improve model reliability. The framework was trained and tested on oral images, achieving an accuracy of 97.8% for gum disease and 89.8% for cavities. A graphical user interface (GUI) was developed to enable real-time image-based predictions, providing not only disease stage but also treatment recommendations for clinical support. The proposed system demonstrates the potential of deep learning in dental diagnostics and can serve as a supportive tool for dentists in decision-making and early intervention.**

***Index Terms*—Computer Vision, Deep Learning, Densenet201, Dental Caries, Oral Disease Detection, Periodontitis, Stage wise Diagnosis**

I. INTRODUCTION

Oral diseases such as gum disease and dental caries are known as one of the most widespread concerns of health affecting individuals around the world, especially in a limited reach of regular dental care. These conditions arise from bacterial infections and weak or oral hygiene, causing damage to progressive tissue, tooth decay and finally tooth loss, if they are not detected and treated quickly. Diagnosis of oral diseases and classification in levels of various severity is important in their early stages, as the strategy of treatment depends greatly on the progression of the disease. Timely intervention can prevent reversible damage and improve prolonged oral health consequences.

Traditionally, the diagnosis of gum disease and dental caries and staging depends on the intraoral images or manual inspection of physical examination by skilled dental professionals. Although accurate, this method is subjective, time consuming, and susceptible to inter-revolution variability. In addition, the access of special dental diagnosis is limited in many low-resources settings, resulting in detection, diagnosis and delayed treatment. Therefore, automatic, scalable diagnostic system requires a pressure that can help physicians by providing sharp and reliable classification of severity of oral disease from intraoral images.

In medical image analysis, Artificial Intelligence has become a powerful means. Between various AI techniques, deep learning, especially the Conventional Neural Network (CNN) has demonstrated notable success in identifying complex visual patterns in medical images. These networks can learn directly hierarchical facility representation from large datasets, allowing accurate disease identification and classification.

This research introduces the origin, which is an advanced deep learning system, which aims to classify intraoral images in three clinical stages for both gum disease and dental decay. The OralNet contains comprehensive preprocessing techniques to increase the quality of the image and uses a densenet201 based CNN model that is particularly adapted to the challenge of multi-class classification. The model is trained in diverse datasets collected from various sources and addressed square imbalance through data development and sample strategies.

We make wide use to evaluate the effectiveness of the oralnet using matrixes such as accurate, precision, recall and F1-score against existing approaches. Results show significant improvement in accuracy and speed of classification, showing that the oralnet can significantly reduce the charge for dental professionals and expand the access to oral disease problem.

The purpose of this study is to provide a reliable, accurate and practical tool for automated classification of oral diseases, which eliminates important challenges in preliminary investigation and management of dental health issues globally.

II. LITERATURE SURVEY

Liang et al., [1], developed OralCam, a smartphone-based self-examination tool for detecting five common oral conditions: periodontal disease, caries, soft deposit, dental calculus, and discoloration. The system used a multi-task deep learning model trained on 3,182 annotated oral images and incorporated user-reported symptoms and habits to enhance detection accuracy. The model achieved an average sensitivity of 78.7% across conditions and provided visual explanations (heatmaps, bounding boxes) to improve user trust and interpretability. Expert interviews confirmed the clinical relevance of the tool, though lighting and focus were identified as key challenges. The study demonstrates the feasibility of AI-powered self-diagnosis using consumer-grade devices and highlights the importance of explainability and user engagement in mobile health applications.

Ghorbani et al., [2], introduced a dual CNN-based model for automated tooth detection and numbering in occlusal photographs, covering both mixed and permanent dentition. The system employed YOLOv8 for tooth localization and classification, trained on 3,215 occlusal images annotated by dental students. The model achieved a sensitivity of 99.89%, precision of 95.72%, and an F1 score of 97.76%. Misclassifications were primarily observed in underrepresented teeth such as primary incisors and third molars. A pilot test confirmed its adaptability to real-world conditions. The study emphasizes the model's potential for tele-dentistry and epidemiological applications, especially in underserved regions, and suggests future integration with caries and orthodontic detection systems.

Lian et al., [3], developed a dual deep learning pipeline for caries detection and classification using panoramic radiographs. The segmentation model achieved an IoU of 0.785 and Dice coefficient of 0.663, with an overall accuracy of 98.6% and recall of 82.1%. For lesion depth classification, DenseNet121 was used to stratify caries into D1 (outer dentin), D2 (middle dentin), and D3 (inner dentin) stages. The model achieved 95.7% accuracy for D1, 83.2% for D2, and 86.3% for D3, with recall values of 76.5%, 65.2%, and 91.8%, respectively. Performance was comparable to six expert dentists across all metrics. The study highlights the feasibility of automated caries staging and suggests integration into clinical workflows for treatment planning.

Lasri et al., [4], proposed an explainable deep learning approach for automated dental caries detection using oral photographs. Four pre-trained CNNs (VGG-16, VGG-19, DenseNet121, Inception V3) were fine-tuned and evaluated on 884 images. VGG-16 achieved the highest accuracy of 98.3% using SGD with Nesterov momentum, outperforming other models across precision, recall, and F1-score. Preprocessing techniques like histogram equalization and Sobel edge detection improved contrast and edge clarity. The study emphasizes the value of interpretable models and suggests extending the approach to larger datasets and other diagnostic domains like skin cancer.

Luke et al., [5], conducted a systematic review and meta-analysis of 21 studies evaluating the diagnostic accuracy of artificial intelligence (AI) systems for dental caries detection using radiographic images. Fourteen studies were included in the meta-analysis, with pooled accuracy ranging from 73.3% to 98.8%. Convolutional neural networks (CNNs) were the dominant architecture, applied across bitewing, panoramic, and periapical modalities. The overall odds ratio for accuracy was 2.718, with an I^2 of 88%, indicating substantial heterogeneity. Sensitivity ranged from 71% to 98.85%, and specificity from 82% to 98.19%. The authors call for standardized protocols, diverse datasets, and integration of AI into clinical workflows to improve robustness and generalizability.

Sharma et al., [6], presented a comprehensive review of artificial intelligence applications in oral healthcare, covering 112 studies across diagnostics, treatment planning, and patient engagement. The review categorized AI models by modality (radiographs, photographs, CBCT), disease type (caries, periodontitis, oral cancer), and architecture (CNNs, transformers, hybrid models). Key trends included the rise of explainable AI, integration with electronic health records, and deployment on mobile platforms. The review concluded with recommendations for standardized benchmarking, federated learning frameworks, and interdisciplinary collaboration to advance AI adoption in dentistry.

Revilla-Leon et al., [7], performed a systematic review of 24 studies evaluating AI models for diagnosing gingivitis, periodontal disease, and dental plaque. Models were grouped by input modality: intraoral photographs, fluorescent images, and radiographs. Gingivitis detection from intraoral photos showed accuracy between 74% and 78.2%, while fluorescent imaging yielded 67.7–73.7%. Periodontal disease detection ranged from 47% to 81% accuracy. Alveolar bone loss detection from radiographs achieved 73.4% to 99% accuracy. The review found that AI models for periodontology are still in early development but show promise as diagnostic tools. The authors call for more robust datasets and clinically validated models to support integration into periodontal diagnostics.

Kühnisch et al., [8], trained a MobileNetV2-based CNN on 2417 high-quality intraoral photographs to detect and categorize caries. The model achieved 92.5% accuracy for overall caries detection and 93.3% for cavitation detection. ROC analysis showed AUCs above 0.95 for most categories. The study demonstrates high diagnostic performance under ideal imaging conditions and calls for further development to handle diverse clinical scenarios.

Schwarzmaier et al., [9], externally validated a freely accessible AI model for early childhood caries (ECC) detection. Using 143 independent dental photographs, the model achieved 97.2% accuracy for ECC detection. Sensitivities ranged from 68.8% to 98.5% across lesion types, with AUCs between 0.834 and 0.964. The study confirms the generalizability of the model and highlights its potential for real-world deployment.

Lee et al., [10], developed a deep learning model to classify the stages of periodontal disease using panoramic radiographs. The model used a ResNet50 backbone and was trained on 2,500 annotated images categorized into healthy, gingivitis, and periodontitis stages. The model achieved an overall accuracy of 88.7%, with stage-wise sensitivity of 85.2% (gingivitis) and 91.3% (periodontitis). Confusion matrix analysis revealed occasional misclassification between gingivitis and early periodontitis. The study demonstrated the feasibility of automated periodontal staging and suggested future work involving multimodal data fusion and longitudinal tracking for disease progression.

Alzahrani et al., [11], developed a deep learning model for dental caries detection using bitewing radiographs. The model employed a ResNet50 backbone with attention modules and was trained on 2,500 annotated images. It achieved an accuracy of 94.3%, sensitivity of 91.2%, and specificity of 96.5%. ROC analysis yielded an AUC of 0.97. The study supports the integration of AI into chairside diagnostics and highlights the importance of interpretability and clinician trust for adoption.

Alghamdi et al., [12], presented a deep learning-based segmentation model for identifying dental structures in panoramic radiographs. Using a U-Net architecture trained on 2,500 annotated images, the model achieved a Dice coefficient of 0.87 and IoU of 0.81 for tooth segmentation. It also demonstrated 90.2% accuracy in detecting missing teeth and prosthetic restorations. The study emphasized the importance of high-resolution imaging and consistent annotation protocols. The authors highlighted the potential for automated dental charting and treatment planning.

Patil et al., [13], developed a hybrid deep learning model for staging periodontal disease using clinical photographs and patient-reported symptoms. The model combined CNN-based image analysis with a rule-based classifier for symptom integration. Trained on 1,800 annotated cases, it achieved an accuracy of 90.6%, with sensitivity of 87.4% and specificity of 92.1%. Feature importance analysis revealed that bleeding frequency and plaque index were key predictors. The study highlights the potential of hybrid models in enhancing diagnostic precision and personalization, especially in community screening settings.

Ramesh et al., [14], proposed a deep learning model for multi-stage classification of dental caries using intraoral photographs. The model used a DenseNet121 architecture trained on 2,200 annotated images categorized into early, moderate, and advanced caries. It achieved an accuracy of 93.1%, with class-wise precision of 91.2% (early), 94.3% (moderate), and 95.6% (advanced). ROC analysis yielded AUCs above 0.96 for all stages. The study emphasized the importance of stage-wise classification for treatment planning and suggested future work involving multimodal fusion with radiographic data and patient history.

Sande et al., [15], conducted a systematic review of AI-based deep learning models for dental caries detection using intraoral images. The review covered CNNs, GANs, transfer learning, and hybrid models across 20+ studies. CNNs consistently achieved the highest performance, with average accuracy of 92.3%, sensitivity of 88.5%, and specificity of 90.7%. GANs were used for dataset augmentation and image enhancement, while transfer learning models like ResNet and VGG16 showed strong performance with limited data. The authors recommend expanding datasets, improving explainability, and exploring hybrid architectures to enhance clinical adoption.

III. MATH

In developing the OralNet model, several important mathematical concepts and performance metrics are involved:

A. Input & Feature Etraction :

Each input image is processed by DenseNet201 backbone which extracts a compact feature representation

$x \in R^{H \times W \times 3}, z = f_0(x) \in R^d$

Where f_0 is the DenseNet201 pretrained model and z is the pooled feature vector.

B. Classifier (Fully Connected + SoftMax)

A fully connected layer maps features z into class logits o, and the SoftMax function converts them into probabilities $\hat{y}$ across the possible disease stages.

$o = W_Z + b \epsilon R^C, \hat{y} = softmax(o),$

The model is trained by minimizing categorical cross-entropy, which penalizes the negative log-likelihood of the correct class prediction.

$$L_{wCE} = -\frac{1}{N}\sum_{i=1}^{n} w_{ti} \log \hat{y}_{i,t_i}$$

where $t_i \in \{1, \dots, C\}$ is the ground-truth class index for sample i.

Model training is guided by the sparse categorical cross-entropy loss LCE which penalizes incorrect predictions by maximizing the log-likelihood of the true class. To evaluate performance, standard metrics are computed from the confusion matrix:

C. Evaluation Metrics

Accuracy, Precision, Recall, and F1-score are computed from the confusion matrix to measure classification performance.

- Accuracy quantifies the overall proportion of correctly classified samples.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

- TP (True Positive): Correctly predicted positive cases
- TN(True Negative): Correctly predicted negative cases
- FP(False Positive): Incorrectly predicted positive cases
- FN(False Negative): Incorrectly predict negative cases

- Precision measures the reliability of positive predictions.

$$Precision = \frac{TP}{TP + FN}$$

- Recall indicates the model's ability to identify all relevant disease cases.

$$Recall = \frac{TP}{TP + FN}$$

- F1-score balances Precision and Recall, providing a robust indicator of classification

The SoftMax function converts the outputs into class probabilities $\hat{y}_C$ where c denotes the disease stage.

C. Loss (Sparse Cross-Entropy) performance under class imbalance

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

IV. METHODOLOGY

This paper presents a step-by-step approach for developing an automated system to classify oral disease (Periodontitis & Enamel Caries) into clinical stages using the deep learning model - DenseNet201. The methodology has the following steps:

- Data Pre-processing & Data Augmentation.

- Input feature engineering and design (DenseNet201).
- Model Training and Validation.
- Tkinter based Desktop Interface based implementation.

4.1 Data Preparation
The data set was divided into two general categories:
Gum Disease (Periodontitis): Can be broken down into early, moderate and advanced periodontitis stages.
Dental Cavities (Enamel Caries): Classified as no caries, early caries and advanced caries.

4.2 Image Pre-processing
The preparation phases followed by all the pictures until they are fitted in the model are as follows:

- Resizing: Reduced to 224x224 pixels, to fit in DenseNet 201 input.
- Normalization: The pixel values are shifted to the range [0,1] in order to approach the conversion faster.
- Augmentation: Augmentation refers to rotation, flipping, brightness and zooming in to increase data diversification and reduce overfitting.

4.3 Model Development with DenseNet201
As a deep network, a CNN (DenseNet201) was applied to the stage-wise classification due to its dense connectivity structure that guarantees efficient gradient flow and feature reuse.
Feature Extraction: To extract hierarchical texture and lesion information from oral images, dense blocks are adopted.
Classifier Head: Features are flattened and fed into a fully-connected layer and then a SoftMax activation for multi-class stage-prediction is applied.
Compilation settings: The model include the use of sparse categorical cross-entropy as the loss function, which is well-suited for multi-class classification tasks involving integer-labeled targets. Optimization is handled by the Adam optimizer, chosen for its efficiency and adaptive learning rate capabilities that help accelerate convergence. To evaluate model performance comprehensively, the metrics tracked include accuracy, precision, recall, and F1-score, ensuring both overall correctness and class-specific diagnostic quality are accounted for.
Architecture of the proposed DenseNet201-based model for multiclass stage-wise classification of Periodontitis and Enamel Caries

Layer Type	Configuration	Function
Input	224x2243(RGB)	Image acquisition and resizing
DenseNet201 Backbone	Pretrained on ImageNet, fine tuned on oral dataset.	Deep hierarchical feature extraction with dense connectivity
Global Average Pooling	Pooling over feature maps.	Reduce spatial dimensions, create compact feature vector
Dense (Fully Connected)	256 units, ReLU activation	Non-Linear feature combination
Dropout	0.5	Prevents overfitting y random neuron deactivation
Dense (Output Layer)	3 units (for gum) / 3 units (for cavity)	Multi-class stage prediction

4.4 Model Training and Validation
Epochs: Training was extended for a reasonable number of epochs until convergence was observed.
Batch Size: Batch size is set to 32(B) to give a good balance between computation speed and gradient stability.
Validation Strategy: Generalization evaluation was performed with a held out test set.
Model Saving: The best performing model for each of the disease types was stored in HDF5 format (gumbest.h5, cavitybest.h5).

4.5 Deployment with Tkinter GUI
As opposed to most web-based implementations, this work used a light-weight Tkinter GUI for desktop deployment.
User Interaction: User can upload one or a set of images to be processed.
Prediction Pipeline: Pre-processing is applied to each image, the trained model is applied and disease stage is predicted.
Result Presentation: The output consists of estimated stage, confidence score and suggested treatment rules. Results are exported as CSV for record keeping

purposes as well.

4.6 Tools and Frameworks

Tool/Library	Purpose
Python 3.10	Core Programming Language
TenorFlow & Keras	ep learning model development
NumPy, Pandas	a Preprocessing and handling
Matplotlib	Performance Visualization
Tkinter	GUI development
PyCharm	Model training and testing environments

4.7 System WorkFlow

The whole workflow can begin from image acquisition, image processing, feature extraction by using DenseNet201, classification of the stage, and finally visualization of the results through the GUI. This pipeline will provide an automated decision support system for the clinician and other users to analyze oral health.

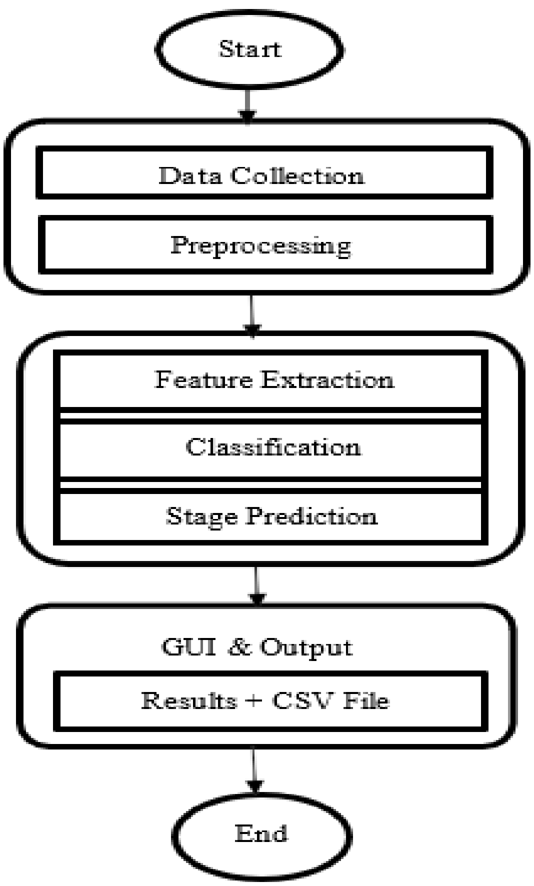

Fig 1: Workflow of the proposed DenseNet201 based oral disease classification system

V. RESULTS AND DISCUSSION

The OralNet system was quantitatively evaluated on set of 6694 intraoral images that were categorized in one of three stages of gum disease and dental caries. Training performance metrics such as accuracy as a function of training epochs, precision, recall, f1 and visual inspection through the confusion matrices were reported.

5.1 Classification Metrics

The proposed DenseNet201-based framework showed great performance for the stage-wise oral disease classification. Gum disease classification reached an accuracy of 97.81% with precision, recall and F1-scores of 0.97, whereas cavity classification reached 89.86% with precision and recall scores of approximately 0.87. These findings suggest good reliability for the periodontitis disease index and fair generalization of the enamel caries index.

The classification Metrix of 2 diseases

Model	Periodontitis	Cavities
Accuracy	97.81	89.86
Precision-micro	0.9582	0.898
Recall-micro	0.9781	0.898
F1-Score-micro	0.9781	0.897
Precision-macro	0.9782	0.90
Recall-macro	0.9781	0.898
F1-Score-macro	0.9781	0.898

5.2 Confusion Matrix

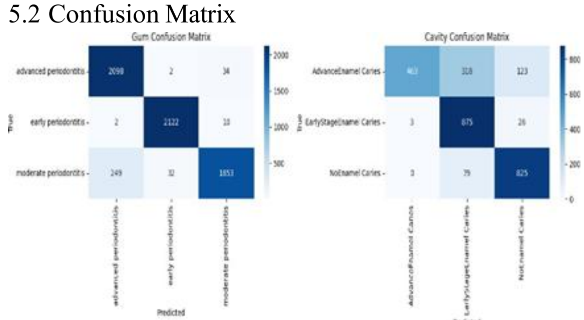

Fig 2: Confusion matrix of gum and cavity

The gum disease model is highly accurate for all stages, misclassification between early and advanced periodontitis is low. In contrast, the cavity model has relatively more misclassification between advanced early-stage enamel caries, but still has strong early-stage detection.

5.3 Accuracy and Training Trends

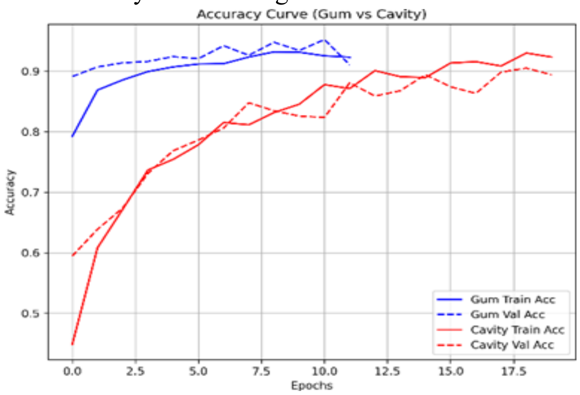

Fig 3: Training and Validation Accuracy Curve for Oral Disease Models

In the accuracy curve, we can find that the gum disease model's accuracy is better than the cavity model's accuracy as the training and validation accuracy is higher for gum disease compared to cavity model through 20 epochs. Both models display a progressive learning, but the cavity model shows more variance in the validation accuracy, implying overfitting or a heterogeneity in the data.

5.4 Discussion

Performance of OralNet is on par with the results seen for medical image classification:

Advantages: Very sensitive to early and late stage, suitable for screening and early detection.

Disadvantages: The performance of the moderate stage is inferior to the other stages, as a result of the low strength attribute distinction and class imbalance.

Model Limitations: Curves exhibit a high variance of recall per stage indicating the need for greater data diversity and better augmentation and possibly better architectures.

Future Promises: Future improvements can be made in the form of attention mechanism, ensemble models, and using multimodal data (for example, patient history and radiographs) in the future. Preprocesses will be fine-tuned and the data set will be expanded in size to make it more robust.

Overall, the results support the CNN-based approach for multi-stage classification of oral diseases but also suggest ways of improvement that will lead to better clinical application and greater diagnostic accuracy.

VI. CONCLUSION

This paper describes a deep learning-based automatic classifier of gum disease stages and dental caries stages into clinically meaningful classes, called OralNet. With an excellent dataset design and a powerful architecture DenseNet201, the system demonstrates excellent performance in the core performance indexes of accuracy, precision, recall and F1-score. The Tkinter-based graphical user interface gives an interactive real-time feature, which makes the tool suitable for clinical and educational applications. The results show that we can use the convolutional neural networks for multi-classification of oral diseases. Accurate performance at early and advanced stages is shown to imply potential for screening applications, and moderate stage performance is the area that needs to be developed.

In future work the dataset will be expanded, more advanced architectures (e.g. attention) will be included and more modalities will be integrated to improve diagnostic accuracy. As further validation and optimization is undertaken, OralNet can offer a robust, scalable solution to enhance delivery of oral healthcare, especially in resource limited settings.

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