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Enhancing the Image-Based Gingivitis Disease Detection System Using Deep Learning Approach

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ABSTRACT: Gingivitis is one of the most prevalent oral health conditions worldwide and represents an early stage of periodontal disease. If not detected and treated promptly, gingivitis may progress into periodontitis, leading to severe gum damage, tooth loss, and systemic health complications. Traditional diagnosis of gingivitis requires clinical examination by dental professionals, which is often inaccessible in remote or underserved regions. This paper presentsEnhancing The Image Based Gingivitis Disease Detection System Using Deep Learning Approach , an intelligent web-based system for automated detection of gingivitis using deep learning techniques. The system employs a fine-tuned EfficientNet-B1 convolutional neural network architecture for binary classification of gum health conditions into two categories: healthy gums and gingivitis. The model was trained on a curated dataset of 2,800 oral images, utilizing data augmentation strategies including rotation, zooming, brightness adjustment, and horizontal flipping. The model achieved a test accuracy of 90% and a ROC-AUC score of 0.956, demonstrating reliable discriminative capability. The trained model is integrated into a Flask-based REST API backend paired with an HTML/JavaScript frontend, enabling users to upload gum images and receive real-time classification results with confidence scores. Gingivitis Disease Detection System provides a practical and efficient solution for preliminary gum health screening and clinical decision support.
Keywords: Gingivitis Detection, EfficientNet-B1, Deep Learning, Convolutional Neural Network, Transfer Learning, Oral Health, Medical Image Classification, Flask API, Web Application

I. INTRODUCTION

Oral health plays a critical role in overall human health and well-being. Among the various dental diseases, gingivitis is one of the most common inflammatory conditions affecting the gums globally. Gingivitis is primarily caused by the accumulation of bacterial plaque around the gum line, which leads to inflammation, redness, swelling, and bleeding. If not diagnosed and treated in its early stages, gingivitis can progress into periodontitis — a more severe form of gum disease that damages the soft tissue and bone supporting the teeth. Periodontitis has been associated with systemic diseases such as cardiovascular disease, diabetes, and respiratory infections.

Despite the importance of early detection, gingivitis often goes unnoticed because its symptoms are mild during initial stages. Many individuals fail to recognize early warning signs and seek treatment only when the condition becomes severe. Traditional diagnosis requires examination by a trained dental professional using clinical inspection and specialized instruments — a method that is effective yet limited by accessibility, cost, and dependency on clinical infrastructure. In many rural or underdeveloped regions, access to dental healthcare is constrained, which increases the risk of untreated gum diseases.

Recent advancements in artificial intelligence (AI) and deep learning have opened new possibilities in medical image analysis and automated disease detection. Convolutional Neural Networks (CNNs) have demonstrated remarkable success in analyzing medical images such as skin lesions, retinal scans, chest X-rays, and oral images. In the context of dental healthcare, deep learning techniques can be applied to analyze images of gums and detect signs of inflammation or abnormalities.

The GumCheck Gingivitis Detection System is developed to leverage the EfficientNet-B1 architecture — a modern CNN known for high accuracy and computational efficiency — trained on a gum image dataset using transfer learning and fine-tuning. The system is deployed in a Flask-based web application that allows users to upload gum images and receive predictions in real time. The significance of this project lies in its potential to enhance early detection of gingivitis, support preventive dental care, and assist dental professionals in diagnostic decision-making.

II. LITERATURE SURVEY

A. Background
Automated detection of oral diseases using computational approaches has gained increasing research interest over the past decade. Early studies primarily relied on conventional image processing techniques such as color histogram analysis, edge detection, and texture-based feature extraction to distinguish between healthy and diseased gum conditions. While these approaches demonstrated feasibility, they were often limited by sensitivity to illumination variations and the inability to capture complex non-linear feature relationships.

B. Deep Learning for Medical Image Analysis
With the proliferation of large-scale annotated medical image datasets and advances in GPU computing, deep learning architectures have become the dominant paradigm for medical image classification. Rajpurkar et al. (2017) demonstrated that deep convolutional networks could achieve radiologist-level accuracy in detecting pneumonia from chest X-rays. Similarly, Esteva et al. (2017) applied CNNs for dermatologist-level classification of skin cancer from clinical images, achieving performance comparable to board-certified dermatologists. These works established the viability of CNNs for automated medical diagnosis.

C. EfficientNet and Transfer Learning
Tan and Le (2019) introduced the EfficientNet family of convolutional neural networks, proposing a compound scaling methodology that uniformly scales network depth, width, and image resolution. EfficientNet-B1 achieves state-of-the-art accuracy on ImageNet while maintaining computational efficiency compared to conventional architectures like ResNet and VGG. Transfer learning using ImageNet pretrained weights has been widely adopted in medical imaging tasks to overcome the challenge of limited labeled data, as demonstrated in multiple studies across radiology, pathology, and dermatology domains.

D. Oral Disease Detection
Research specifically targeting oral disease detection using AI is comparatively sparse but growing. Jiang et al. (2021) applied CNNs to classify periodontal disease from intraoral photographs, achieving accuracy above 85%. Lee et al. (2020) investigated the use of deep learning for caries detection from dental radiographs, reporting promising sensitivity and specificity. Jain et al. (2022) explored classification of oral lesions using pretrained ResNet architectures, achieving competitive results with limited annotated data. However, gingivitis-specific binary classification using EfficientNet-B1 with a curated web-deployable system represents a gap that the present work addresses.

E. Web-based AI Diagnostic Systems
The deployment of AI-based diagnostic systems via web frameworks has been explored in several healthcare domains. Kim et al. (2020) deployed a skin lesion classifier using Flask and demonstrated practical usability for preliminary screening. Similar deployment patterns using REST APIs have been applied in diabetic retinopathy screening tools, highlighting the efficacy of Flask-based backends for real-time inference delivery. The present work extends this paradigm to the oral health domain by combining EfficientNet-B1 inference with a user-friendly HTML/JavaScript frontend.

III. RELATED WORK

Several recent investigations have addressed aspects of automated oral health monitoring and gum disease classification. Ozden et al. (2020) developed a gingivitis scoring system based on pixel-level color analysis of gum photographs and achieved moderate diagnostic accuracy. Tuzoff et al. (2019) demonstrated that Faster R-CNN architectures could localize caries and periapical pathologies in panoramic radiographs with high precision. Nguyen et al. (2021) applied ResNet-50 for multi-class oral lesion classification, achieving 87.3% accuracy on a dataset of 1,400 images.

In terms of mobile and web deployment, Prasetyo et al. (2022) built a mobile application using TensorFlow Lite for real-time classification of gum health conditions, demonstrating the feasibility of edge deployment. Joshi et al. (2021) integrated a VGG-16-based oral disease classifier into a telemedicine platform and validated its utility through a user study in rural India. These works collectively confirm that AI-powered oral health tools are both technically viable and clinically relevant.

In comparison to related systems, GumCheck distinguishes itself through the adoption of EfficientNet-B1 — offering superior accuracy-to-computation ratio — combined with comprehensive data augmentation, a complete end-to-end web deployment pipeline, and empirical validation on a carefully curated 2,800-image dataset.

The system also incorporates confidence score reporting and a modular architecture amenable to future extensibility.

IV. METHODOLOGY

A. Dataset Preparation

The dataset used in this study consists of 2,800 oral images belonging to two classes: Healthy Gums and Gingivitis. The class distribution contains approximately 1,120 healthy images (40%) and 1,680 gingivitis images (60%). The dataset was partitioned into training (1,960 images), validation (420 images), and testing (420 images) sets. This split ensures adequate data for learning while maintaining unbiased evaluation.

All images were preprocessed prior to model input. Preprocessing involved resizing images to 240×240 pixels — the required input dimension for EfficientNet-B1 — converting images to RGB format, and applying EfficientNet-specific pixel normalization (mean subtraction and standard deviation scaling per ImageNet statistics). Data augmentation techniques applied during training include random rotation within ±10 degrees, random zoom within ±10%, horizontal flipping, and brightness adjustment within the range [0.8, 1.2]. These augmentations improve model generalization by simulating variability in real-world image capture conditions.

B. Model Architecture

The EfficientNet-B1 architecture was selected as the backbone model for this study. EfficientNet-B1 uses compound scaling to jointly optimize network depth, width, and resolution, enabling superior performance with reduced parameter count. The model was initialized with ImageNet pretrained weights to leverage rich feature representations learned from 1.2 million images. The top classification layers were removed and replaced with a Global Average Pooling layer, a fully connected dense layer with 512 units and ReLU activation, a dropout layer (rate=0.3) for regularization, and a final dense output layer with sigmoid activation for binary classification.

During transfer learning, the pretrained EfficientNet-B1 backbone was initially frozen to train only the newly added layers. Subsequently, fine-tuning was performed by unfreezing the top 20 layers of the backbone and continuing training at a reduced learning rate of 1e-5. The Adam optimizer with binary cross-entropy loss was used throughout training.

C. Training Configuration

Hyperparameter	Value
Input Resolution	240 × 240 pixels
Batch Size	32
Initial Learning Rate	1e-4
Fine-tuning Learning Rate	1e-5
Epochs (Transfer Learning)	20
Epochs (Fine-tuning)	15
Optimizer	Adam
Loss Function	Binary Cross-Entropy
Dropout Rate	0.3
Activation (Output)	Sigmoid

V. SYSTEM ARCHITECTURE

The Gingivitis Disease Detection System system follows a three-layer client-server architecture comprising the Presentation Layer, Application Layer, and Machine Learning Layer. The architecture diagram below illustrates the data flow from user input through prediction and result delivery.

USER INTERFACE (Web Browser)
HTML / CSS / JavaScript Frontend
HTTP POST Request (Image Upload)
REST API Communication
FLASK BACKEND SERVER (Python)
API Endpoint: /predict

IMAGE PREPROCESSING MODULE
Resize: 240x240 | Normalize | RGB Convert
EFFICIENTNET-B1 MODEL
Transfer Learning | ImageNet Weights | Fine-Tuned
PREDICTION ENGINE
Sigmoid Activation | Threshold: 0.5 | Confidence Score
JSON RESPONSE
Class Label | Probability | Confidence %
RESULT DISPLAY
Visual Output to User | Probability Bars

Fig. 1. System Architecture of GumCheck Gingivitis Detection System

A. Presentation Layer

The presentation layer consists of the web interface built with HTML5, CSS3, and JavaScript. It enables users to upload oral images through a drag-and-drop or file selection interface. A real-time image preview is displayed before submission. Upon receiving prediction results from the backend, the layer renders the classification label, confidence percentage, and probability distribution bars for both classes.

B. Application Layer

The application layer is implemented using the Flask web framework in Python. It exposes a REST API endpoint (/predict) that accepts HTTP POST requests containing multipart image data. Upon receiving a request, the server validates the image format, initiates preprocessing, performs model inference, and returns a structured JSON response containing the predicted class label, raw probability value, and confidence score. Flask-CORS is configured to enable cross-origin requests from the frontend.

C. Machine Learning Layer

The machine learning layer contains the trained EfficientNet-B1 model serialized in Keras HDF5 format (.h5). The model is loaded into memory at server startup to minimize latency during inference. Preprocessing functions from the tensorflow.keras.applications.efficientnet module are applied to normalize input images consistently with the model's training distribution. Inference is performed using a single forward pass through the model, with the sigmoid output interpreted against a threshold of 0.5 to determine the final class label.

VI. IMPLEMENTATION DETAILS

A. Backend Implementation

The backend server is developed in Python 3.8+ using Flask 3.0. The prediction endpoint receives the uploaded image file via request.files, validates the format against an allowlist (JPEG, PNG, BMP, WebP), and passes the validated image to the preprocessing pipeline. TensorFlow 2.15 and the Keras high-level API are used for model operations. Pillow 10.0 handles image I/O operations including format conversion and resizing. NumPy 1.24+ manages array operations for preprocessing and output processing.

B. Frontend Implementation

The frontend interface is implemented in vanilla HTML5 and JavaScript without additional framework dependencies, ensuring fast load times and broad browser compatibility. Fetch API is used for asynchronous communication with the Flask backend. The interface provides visual feedback including upload progress indicators, image previews, and animated result display components. CSS flexbox layout ensures responsive rendering across desktop and mobile screen sizes.

C. Model Training Environment

Model training was conducted in Jupyter Notebook using Python 3.8, TensorFlow 2.15, and Keras. Training was performed on a system equipped with an NVIDIA GPU. The ModelCheckpoint callback saved the best model weights based on validation accuracy, and EarlyStopping with patience=5 prevented overfitting. Training and validation loss and accuracy curves were monitored to assess convergence behavior.

D. Deployment

The Flask application is deployed as a standalone server accessible via a web browser. The trained model file (gumcheck_efficientnetb1.h5) is loaded at application startup and held in memory for inference. The system supports concurrent requests through Flask's built-in development server and can be scaled using production-grade WSGI servers such as Gunicorn. The application is containerizable using Docker for cloud deployment to platforms such as AWS EC2, Google Cloud Run, or Azure App Service.

VII. RESULTS & DISCUSSION

A. Classification Performance

The trained EfficientNet-B1 model was evaluated on the held-out test set of 420 images. The model achieved an overall accuracy of 90.0%, with balanced precision, recall, and F1-score values for both classes. The ROC-AUC score of 0.956 indicates strong discriminative capability between healthy and gingivitis classes.

Metric	Value
Test Accuracy	90.0%
Precision (Macro Avg)	0.90
Recall (Macro Avg)	0.90
F1-Score (Macro Avg)	0.90
ROC-AUC Score	0.956
Test Dataset Size	420 Images

Table I. Classification Performance Metrics on Test Dataset

B. Confusion Matrix

Actual / Predicted	Healthy	Gingivitis
Healthy	154 (TP = 154)	14 (FP = 14)
Gingivitis	30 (FN = 30)	222 (TN = 222)

Table II. Confusion Matrix for Test Dataset

The confusion matrix reveals that 154 healthy samples and 222 gingivitis samples were correctly classified. Fourteen healthy images were incorrectly predicted as gingivitis (false positives), and 30 gingivitis images were incorrectly predicted as healthy (false negatives). The slightly higher false negative rate may be attributable to mild gingivitis cases that exhibit visual characteristics closely resembling healthy gums, underscoring the need for diverse and well-annotated training data.

C. Comparison with Related Models

Model	Accuracy	Dataset Size
VGG-16 (Joshi et al., 2021)	84.5%	1,200 images
ResNet-50 (Nguyen et al., 2021)	87.3%	1,400 images
MobileNet-V2 (Prasetyo et al., 2022)	85.0%	1,800 images
EfficientNet-B1 (GumCheck)	90.0%	2,800 images

Table III. Comparison of Gingivitis Disease Detection System with Existing Models

As shown in Table III, Gingivitis Disease Detection System achieves superior accuracy compared to related systems that employed VGG-16, ResNet-50, and MobileNet-V2 architectures on similar oral health classification tasks. The improvement is attributed to EfficientNet-B1's compound scaling, the larger and more diverse training dataset, and the comprehensive augmentation pipeline.

VIII. FUTURE SCOPE

Several promising avenues exist for extending the Gingivitis Disease DetectionSystem. First, expanding the training dataset to include images from diverse demographic groups, imaging devices, and clinical environments would improve generalization across real-world conditions. Collaborations with dental clinics and hospitals could facilitate the collection of larger annotated datasets with verified clinical labels.

Second, extending the binary classification framework to multi-class classification — distinguishing between healthy gums, mild gingivitis, moderate gingivitis, severe gingivitis, and periodontitis — would provide clinically richer diagnostic outputs. This would require dataset expansion with severity-level annotations and potential adoption of ordinal regression techniques.

Third, integrating Explainable AI (XAI) mechanisms such as Gradient-weighted Class Activation Mapping (Grad-CAM) would generate visual saliency maps highlighting the gum regions that influenced the model's prediction. This transparency mechanism is critical for building clinical trust and facilitating model auditing by dental professionals.

Fourth, mobile deployment via TensorFlow Lite or ONNX Runtime would enable on-device inference on smartphones, dramatically improving accessibility for users in low-bandwidth or offline environments. IoT integration with smart oral cameras would further enable remote monitoring and telemedicine applications.

Fifth, incorporation of a patient data management module with longitudinal tracking of gum health records would enable trend analysis, personalized risk assessment, and automated follow-up recommendations, positioning GumCheck as a comprehensive oral health monitoring platform.

IX. CONCLUSION

This paper has presented Gingivitis Disease Detection System, a deep learning-based web application for automated detection of gingivitis from oral images. The system employs EfficientNet-B1, fine-tuned using transfer learning on a curated dataset of 2,800 gum images, and achieves 90% classification accuracy and a ROC-AUC score of 0.956 on a held-out test set. The end-to-end architecture integrates a Flask REST API backend with an HTML/JavaScript frontend, enabling real-time image classification with confidence reporting.

The results demonstrate that GumCheck reliably distinguishes between healthy gums and gingivitis, outperforming related models in the literature. While the system is intended as a decision support tool rather than a clinical diagnostic replacement, it holds significant potential for improving accessibility to preliminary oral health screening in underserved and remote populations.

Future work will focus on multi-class severity classification, Grad-CAM visualization for explainability, mobile deployment, and dataset expansion through clinical partnerships. GumCheck represents a meaningful step toward AI-augmented oral healthcare, demonstrating how deep learning and web technologies can be combined to create practical, accessible, and clinically relevant diagnostic tools.

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