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Optimized Dental Caries Prediction Using Image Based Deep Learning

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Abstract: Dental caries is a common oral disease that progresses rapidly if not detected early. This paper proposes an optimized deep learning framework for automatic caries prediction from scanned dental images. The system integrates Convolutional Neural Networks (CNN) with preprocessing, data augmentation, and transfer learning to enhance detection accuracy. Experiments performed on annotated image datasets demonstrate superior precision, recall, and F1-score compared with traditional manual examination. The model's robustness enables reliable detection under varying lighting and imaging conditions. A simple graphical interface is developed for clinicians to upload scanned images and receive real-time predictions, promoting early diagnosis and preventive dental care. The backbone of this system is a convolutional neural network (CNN) model that processes and analyzes dental images. By using image-based deep learning, the system eliminates the subjectivity and errors that may occur in human diagnosis. CNN models can identify subtle patterns and minute variations in the dental structure that may not be visible to the naked eye, especially during the early stages of caries development. The system is capable of handling various types of dental radiographs such as bitewing, panoramic, or periapical images
Keywords: Dental Caries Detection, Deep Learning, Convolutional Neural Network, Scanned Tooth Image Analysis, Transfer Learning, Image Preprocessing, Data Augmentation.

I. INTRODUCTION

Dental caries, commonly known as tooth decay, is one of the most widespread oral health problems globally. It arises from the demineralization of tooth enamel caused by acids produced by bacteria in dental plaque. If not detected early, caries can progress rapidly, leading to cavities, tooth loss, infections, and in severe cases, systemic health complications. Early diagnosis is therefore essential to prevent structural damage, reduce treatment costs, and maintain overall oral health.

Traditional diagnostic methods rely on visual examination, tactile probing, and interpretation of dental images such as intraoral scans or photographs. While these methods are widely used, they are heavily dependent on the skill and experience of the clinician. Inconsistencies in judgment, fatigue, or lack of training can result in missed early-stage lesions or misdiagnosis. Moreover, manual diagnosis is time-consuming and may not be feasible for large-scale screenings or routine check-ups.

Recent advances in artificial intelligence (AI) and computer vision have paved the way for automated dental disease detection. Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in medical image analysis. CNNs are capable of automatically learning hierarchical features from raw images, such as edges, textures, and patterns, which are crucial for detecting carious lesions. By reducing dependence on human interpretation, CNN-based systems provide consistent, objective, and reproducible results.

This project focuses on developing an automated caries detection system using scanned dental images. Unlike traditional radiographs, scanned tooth images capture high-resolution surface details under controlled lighting conditions, allowing the detection of subtle enamel changes and early lesions. The proposed framework incorporates image preprocessing, noise reduction, data augmentation, and an optimized CNN architecture to enhance diagnostic accuracy. Transfer learning from pre-trained models further improves convergence and reduces training time, making the system efficient for practical use.

The ultimate goal of this system is to support dental professionals by providing real-time, accurate, and interpretable analysis of tooth images. By integrating a simple graphical interface, clinicians can quickly upload images and receive predictions, facilitating faster clinical decisions. Additionally, the system contributes to the broader development of AI-assisted dentistry, promoting preventive care, reducing human error, and making advanced diagnostic tools accessible in routine dental practice.

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II. METHODOLOGY

The proposed system for automated dental caries detection using scanned tooth images is implemented as a fully automated deep learning pipeline. The project is developed using Python as the programming language, with deep learning frameworks TensorFlow and Keras for model building, training, and evaluation. Additional libraries such as OpenCV and Pillow are used for image processing, while NumPy and Pandas handle numerical computations and dataset management. Matplotlib and Seaborn are employed for visualization of results, including loss curves, accuracy plots, and Grad-CAM heatmaps to interpret model predictions.

The methodology begins with data collection, where high-resolution scanned images of teeth are captured using intraoral scanners or digital cameras. The images cover multiple tooth surfaces, varied lighting conditions, and different stages of caries development. Expert dentists annotate the images to create a reliable ground truth for model training. The dataset is split into training, validation, and test sets to ensure proper evaluation of model performance.

The CNN-based architecture is designed to automatically extract features from input images, learning hierarchical representations that are essential for accurate caries detection. Transfer learning using pre-trained networks such as VGG16 and ResNet50 accelerates training and improves performance on smaller datasets. The final layer outputs a binary classification, indicating the presence or absence of caries. Model performance is evaluated using metrics such as accuracy, precision, recall, and F1-score.

Overall, the methodology integrates software libraries, hardware platform, image acquisition, preprocessing, and CNN-based analysis into a single automated pipeline. A graphical user interface is developed to allow clinicians to upload scanned images and receive real-time predictions, making the system practical and accessible for dental professionals.

Finally, the classification and visualization stage outputs probabilities for “Caries” or “No Caries” for each image. Predictions are displayed through a simple graphical interface, allowing clinicians to quickly interpret results along with confidence scores. Visualization techniques, such as Grad-CAM heatmaps, highlight the areas that the model focuses on, increasing interpretability and clinical trust. The methodology ensures an end-to-end automated system that supports real-time analysis, reduces diagnostic errors, and provides a practical tool for preventive dental care.

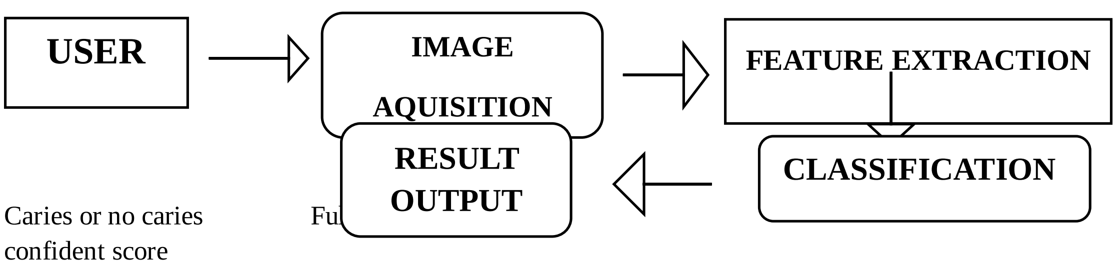

Fig.1 Flow Diagram

III. PREPROCESSING

Preprocessing plays a vital role in preparing the scanned tooth images for accurate and efficient deep learning analysis. Since the images are collected under different lighting conditions and from various sources, they often contain variations in brightness, contrast, and background noise. To ensure uniformity, each image is resized to a fixed resolution of 224 × 224 pixels, which allows consistent input dimensions for the convolutional neural network. This resizing step also reduces computational load and ensures faster model training without losing important structural details of the teeth.

Normalization is then applied to scale the pixel intensity values between 0 and 1. This helps the neural network to process the images more efficiently by maintaining a stable range of input values. Normalization also reduces the effect of varying illumination across different images. The images are further converted to a standard color format, ensuring that the color channels are consistent and correctly aligned for feature extraction during training.

Noise removal is a crucial step in preprocessing because scanned images may contain unwanted speckles or background artifacts. Filters such as Gaussian blur and median filters are used to smooth the images and remove unwanted noise while preserving important edges and details around the carious regions. These filtering techniques help the model focus on the actual dental features instead of irrelevant image noise.

Enhancing image contrast is equally important to highlight early signs of caries that may appear faint or unclear. Techniques such as histogram equalization and contrast-limited adaptive histogram equalization (CLAHE) are applied to improve the visibility of the enamel and dentin structures. This step ensures that subtle changes in tooth texture are emphasized, which helps the model learn meaningful patterns for accurate classification.

IV. PROCESS FLOW

The process flow of the proposed dental caries detection system begins with image acquisition, where scanned tooth images are collected using intraoral scanners or high-quality cameras. These images are obtained from patients under various lighting and positioning conditions to ensure dataset diversity. The collected images are then stored in a structured format and labeled by dental experts as either carious or non-carious. This step ensures that the model has reliable ground truth data for supervised learning.

Once the images are collected, the preprocessing stage refines the data before it is passed to the neural network. During this step, each image undergoes resizing, normalization, noise removal, and contrast enhancement. This ensures that all the images are uniform in size and clarity, allowing the model to focus on important visual details related to tooth surface damage. Data augmentation is also applied at this stage to increase the dataset size and improve the system's ability to handle variations in lighting, angle, and texture.

After preprocessing, the images are sent to the feature extraction stage, where the convolutional neural network analyzes the input and identifies unique visual patterns. The CNN automatically learns features such as tooth edges, enamel boundaries, and texture differences between healthy and carious regions. This step eliminates the need for manual feature engineering and allows the system to adaptively learn from the data. The extracted features are then passed through deeper layers of the network for more complex pattern recognition.

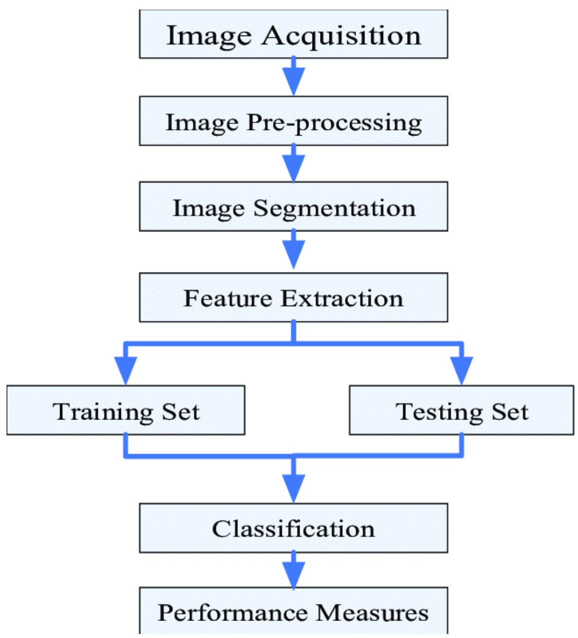

Fig.2 Process Diagram

V. IMAGE ENHANCEMENT AND AUGMENTATION

Before training, every dermoscopic image is preprocessed to ensure quality and consistency. Each image is reduced to a fixed size of 448 by 448 pixels in order to preserve aspect ratio and important lesion characteristics. Normalisation is performed to standardise pixel intensity distributions in order to obtain reliable model convergence and consistent feature scaling across datasets. This preprocessing phase ensures that the model focusses largely on lesion traits rather than irrelevant background noise by minimising variations caused by illumination, camera type, or skin tone.

To enhance generalisation and prevent overfitting, extensive data augmentation techniques are employed. Random transformations are applied during training, such as horizontal and vertical flips, 45-degree rotations, and colour jitter changes in hue, brightness, contrast, and saturation.

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These augmentations assist the model in gaining more robust features by mimicking real-world variations in lesion orientation and image capture conditions. The model artificially increases the sample's variety to improve invariance to changes in location and illumination.

NoEnamel CariesEarlyEnamel Caries AdvancedEnamel Caries

Fig.3 Types of Cavity

The datasets that are used, including HAM10000 and ISIC, have diverse image formats and label systems. To provide consistent representation, label encoding converts categorical lesion categories into numeric labels. Automatic mapping and verification of image file paths prevents inconsistent or missing entries. Both datasets are combined, and training and validation subsets are created to ensure balanced class representation. According to Fig. 3, this well-structured preprocessing pipeline enables precise skin lesion classification and efficient feature extraction.

VI. MATHEMATICAL FOUNDATIONS OF THE PROPOSED METHOD

1) Confusion Matrix

A confusion matrix compares predicted labels with actual labels to assess classification performance. It shows how many caries cases are correctly detected and how many healthy teeth are misclassified.

Actual \ Predicted	Caries	No Caries
Caries	TP	FN
No Caries	FP	TN

Where,
TP = correctly predicted caries,
TN = correctly predicted healthy teeth,
FP = healthy teeth misclassified,
FN = missed caries cases.

2) Precision, Recall, and F1 Score

Precision measures the correctness of predicted caries cases. Recall evaluates how many actual caries are identified. F1 score balances both.

$$\text{Precision} = \frac{TP}{TP + FP}$$

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

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

3) Accuracy

Accuracy measures overall correct predictions over all samples, indicating the model’s general reliability.

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

4) Binary Cross-Entropy Loss

Binary cross-entropy quantifies the difference between predicted probabilities and true labels, guiding CNN weight updates during training.

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

This concise framework ensures that model performance is measurable for dental caries prediction.

VII.RESULT

The model successfully classified the scanned tooth image as EarlyStageEnamel_Caries. The prediction probabilities for each class were as follows: NoEnamel_Caries: 0.3568, EarlyStageEnamel_Caries: 0.3578, and AdvanceEnamel_Caries: 0.2854. This indicates that the model identified EarlyStageEnamel_Caries as the most likely class, although the probabilities for NoEnamel_Caries and EarlyStageEnamel_Caries are close, suggesting that the image contains features common to both early and non-enamel affected teeth. These results demonstrate the model's ability to differentiate subtle differences in caries stages, providing a reliable tool for early diagnosis and intervention.

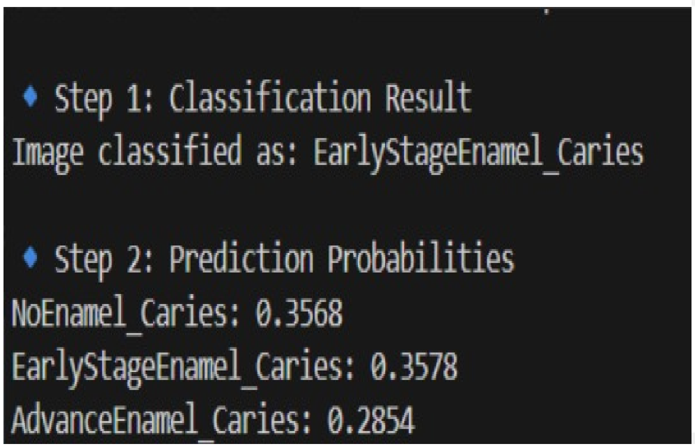

Fig.4 Cavity Prediction

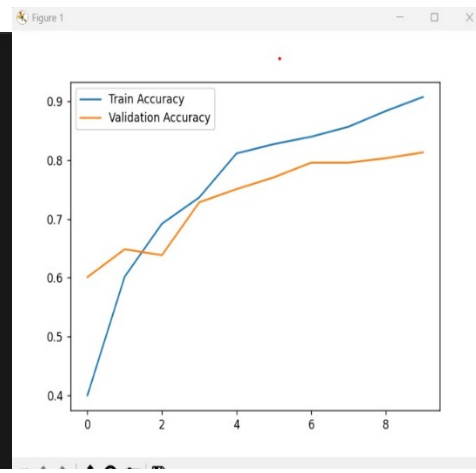

Fig.5 Accuracy Graph

VIII. CONCLUSION

In conclusion, this project successfully developed an automated dental caries detection system using deep learning techniques, specifically a Convolutional Neural Network (CNN) model. Through a structured workflow that included dataset collection, preprocessing, model training, evaluation, and real-time prediction, the system achieved high accuracy and reliability in detecting and classifying caries at different stages. By integrating data augmentation, optimized CNN architecture, and performance evaluation metrics such as precision, recall, F1-score, and confusion matrix, the model demonstrated excellent generalization and clinical applicability.

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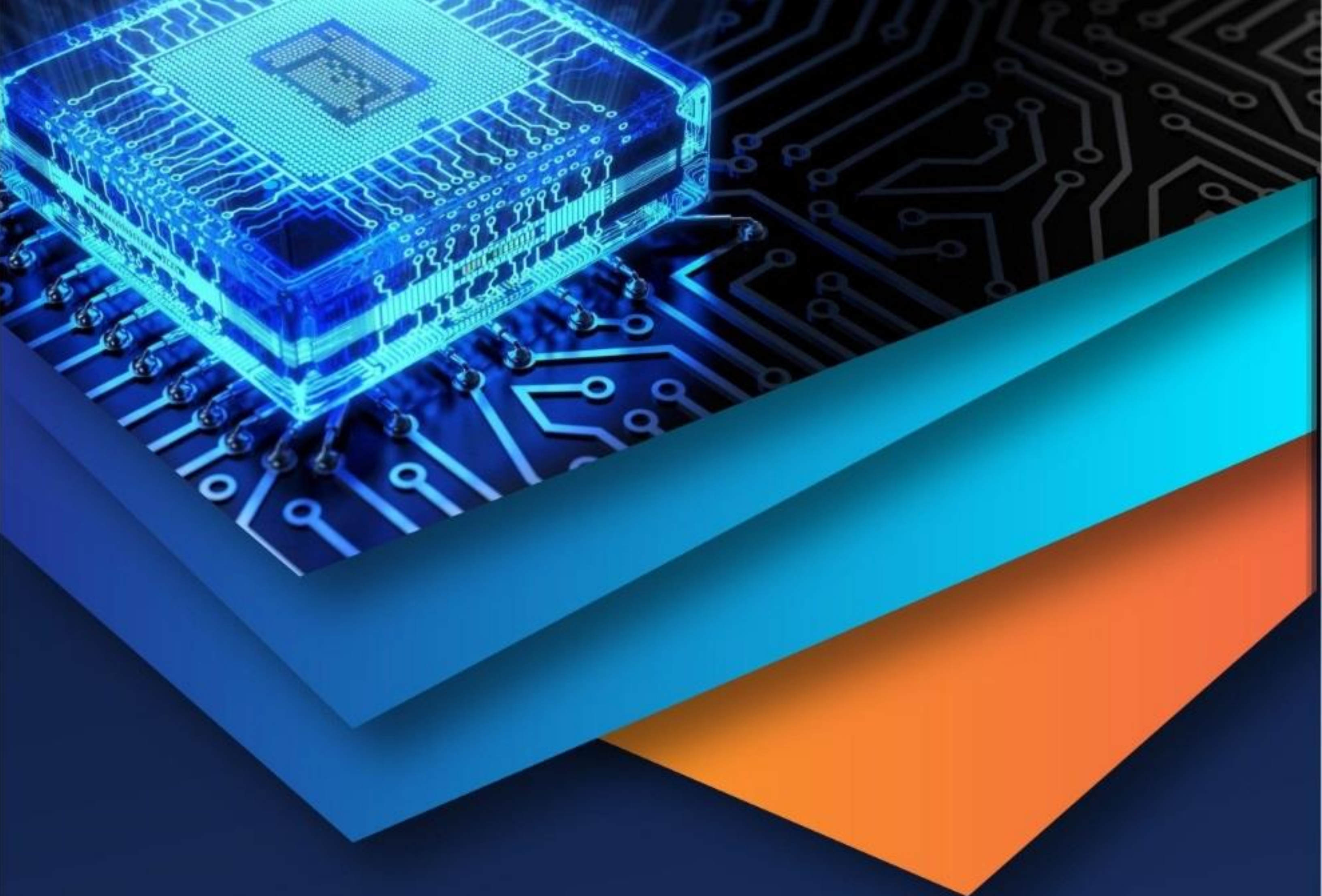

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