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Automated Detection of Dental Caries Using Deep Learning Models

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Abstract

Dental caries is a disease that is common worldwide. Dental caries remains one of the most prevalent oral diseases globally, necessitating accurate and early detection to enable timely interventions and preserve tooth structure. This study presents a lightweight and task-specific Convolutional Neural Network (CNN) architecture, called DentalNet-Lite, designed for the multiclass classification of 1200 RGB intraoral images into three diagnostic categories: normal tooth, early dental caries, and advanced dental caries. The model DentalNet-Lite is a custom CNN designed for the automated detection of dental caries. The model was trained and evaluated, benchmarked against five pretrained CNNs: MobileNetV2, DenseNet121, ResNet50V2, Xception, and InceptionResNetV2. employing accuracy, precision, recall, and F1-score as evaluation criteria. DentalNet-Lite achieved a test accuracy of 99.07%, exceeding all competing approaches while maintaining low computing complexity, hence demonstrating its suitability for real-time, resource-limited clinical applications.

Keywords: Dental Caries, Deep Learning, Convolutional Neural Networks (CNN), AI in Dentistry, Early Detection.

1. INTRODUCTION

Dental caries is a disease that is common worldwide [1]. Dental caries is considered as one of the most prevalent oral diseases worldwide, impacting approximately 60–90% of school-aged children and a large proportion of adults[2]. According to the World Health Organization (WHO), dental caries (tooth decay) is defined as the degradation of the enamel layer of the tooth due to acids generated by bacterial action on sugars, thereby categorizing it as one of the most prevalent non-communicable diseases (NCDs). This suggests that the decline in dental health will ultimately result in an increased incidence of tooth loss [3–5]. Conventional techniques for detecting dental caries predominantly depend on clinical assessments conducted by dentists, using instruments such as dental probes, mirrors, and radiographic imaging (e.g., panoramic X-rays or color intraoral Images RGB). Although these procedures are helpful in numerous instances, they encounter considerable constraints, such as reliance on the examiner's expertise, imaging quality, and probable tissue overlap that may mask lesions. These factors increase the risk of diagnostic errors or inconsistencies, underscoring the need for more objective, efficient, and accurate diagnostic approaches. If it can be detected early, minimally invasive treatment is possible, which can contribute to tooth substance preservation more conservatively and effectively [6]. Therefore, this technique was recommended as a minimally invasive treatment by preempting surgical intervention among some non-cavitated caries [7]. Artificial intelligence (AI) techniques and, particularly, deep neural networks have recently brought about a significant transformation in the field of medical diagnosis and treatments, surpassing human performance in various instances through the analysis and extraction of key features from images [8–10]. The use of a convolutional neural network (CNN), a deep learning (DL) algorithm, is a very efficient method for image data processing [11–12]. With the application of CNN, the development of medical decision support systems has become a topic of interest in both the medical academia and industry [13] . This trend is also true for the field of dentistry. Given the crucial impact of oral health on individuals' overall quality of life, dentistry plays a vital role in the digestive process and in enhancing an individual's facial aesthetics and self-assurance [14]. Radiological interpretation and visual and tactile examination are the most common ways for dental professionals to diagnose caries. These procedures are mostly based on clinical experience, which means that different persons may obtain different results; hence, there arises a need for an artificial intelligence-based diagnostic system to support clinical decision-making and assist in the training of new dentists. Deep learning, a type of artificial intelligence (AI), has recently become a feasible approach to automatically and reliably discover tooth decay by looking at dental images.

2. RELATED WORK

Several studies from the last few years have looked into how convolutional neural networks (CNNs) can be used to find and classify the dental caries. Priyanka A et al. (2025) performed a systematic analysis of 14 studies that used AI methodologies for predicting Early Childhood Caries (ECC) through diverse colored image datasets. Significant outcomes comprise: 587 smartphone color images using SVM, achieving 88.76% accuracy. 3,000 periapical radiographs using CNN, achieving 89% accuracy. 2,417 intraoral photographs using CNN, achieving 93.3% accuracy. 45 primary molar images with occlusal caries using ANN, achieving 99% accuracy. 226 extracted teeth with near-infrared imaging using ResNet50, resulting in an accuracy of 74%. Kaggle dataset images using a Convolutional Neural Network, attaining an accuracy of 71.43%. The review affirms that deep learning, particularly CNN and ANN, has superior diagnostic efficacy utilizing colored dental images, with significant potential for individualized and early detection of caries in children[15]. Syed Muhammad Faizan Ahmed et al. (2025) presented the inaugural publicly available annotated intraoral image dataset aimed at AI-based dental caries detection. The collection comprises 6,313 colored photographs (RGB) of individuals aged 10 to 24, gathered in Mithi, Sindh, Pakistan, and annotated useing software, validated by professional dentists. The annotations were transformed into YOLO, COCO, and PASCAL VOC formats. Five AI models were assessed, with YOLOv8s attaining the superior performance (mAP = 0.841 at 0.5 IoU). Images were captured from diverse intraoral views, using both cheek retractors and without. The dataset seeks to enhance automated caries detection with deep learning algorithms [16]. Rouhbakhshmeghrazi et al. (2024) performed a study using 500 RGB color images obtained through an intraoral camera for six months. The research employed the YOLOv8 object detection algorithm, with the YOLOv8s variant achieving the best performance: (84%) precision, (79%) recall, and (85% mAP@0.5). The research emphasizes the efficacy of color images for the early identification of tooth caries and the prospective establishment of a mobile oral healthcare system[17]. In 2024, Shima Minoo et al. conducted a study for the classification of dental diseases: Calculus, Tooth Discoloration, and Caries using 3392 RGB images. The authors employed three CNN architectures: VGG16, VGG19, and ResNet50.ResNet50 attained the highest performance with an accuracy of 95.23%, indicating its potential as the optimal model for clinical dental diagnostics[18]. Sohee Kang et al. (2024) performed a study using 2,682 color (RGB) intraoral images for the identification of dental caries. The authors utilized deep learning models such as ResNet50, Inceptionv3, and Inception-ResNetv2. The model that worked best, Inception-ResNetv2, got an accuracy of 94.4%.The work shows how deep CNN models could help diagnose caries using (RGB) intraoral images[19].Yanshan Xiong et al. (2024) conducted a pilot study using (1020) color (RGB) intraoral images from (762) volunteers to simultaneously detect dental caries and fissure sealants. They developed a deep learning model called ToothNet on a revised version of the YOLOX framework. at the image level ,ToothNet achieved an AUC of 92.50% for caries detection and 90.20% for sealants . At the tooth level, its F1-score for caries detection was (81.00%), outperforming a dentist with (1 year) of experience. The research illustrates the efficacy of multi-task deep learning models in intelligent dentistry diagnosis[20]. Carneiro et al. (2024) looked closely at how deep learning can be used in dental radiography, focusing on how to determine, separate, and classify teeth, caries, and restorations. Of the 393 papers that were located, 68 were good enough to be included. This means that AI is growing better at spotting problems in dental health imaging [21].Niha Adnan et al. (2024) developed a based on artificial intelligence mobile applicationfor dental caries detection using 7,465 colored intraoral images. The YOLOv5s model was trained, achieving 90.7% precision, 85.6% sensitivity, and an F1-score of 88.0%, outperforming junior dentists. A Detection Transformer was additionally fine-tuned for comparative analysis. The annotated dataset and application of explainable AI facilitated a comprehensive evaluation. The research indicates that this methodology may facilitate the evaluation of caries indices at the population level [22]. Parsa ForouzeshFar et al. (2024) performed a study to diagnose dental caries using 713 bitewing radiographic images collected from the Samin Maxillofacial Radiology Center in Tehran. The dataset consisted of 6032 pictures after preprocessing. The authors used four CNN architectures: VGG16, VGG19, DenseNet121, and ResNet50. Among them, VGG19 had the best accuracy of (93.93%). These results support the feasibility of developing AI-based diagnostic tools for automatic caries diagnosis from radiographs, potentially implementable through mobile applications or cloud-based systems[23]. Researchers Pérez de Frutos et al, (2024) used (13.887) bitewing radiographs from the (HUNT4) Oral Health Study to train and test three deep learning architectures YOLOv5, Retinanet (Resnet50) and EfficientDet (D0, D1) to find proximal caries. The YOLOv5 model showed the highest performance, achieving a mean average precision (mAP) of (0.647), F1-score of (0.548), and false negative rate of (0.149), which is the best, The study demonstrates that AI can effectively assist in caries diagnosis [24]. Toshiyuki Kawazu et al. (2024) conducted study using domain-specific transfer learning to detection dental caries from (1094) intraoral images and (50) simulated panoramic images. A CNN architecture with three convolution and max-pooling layers was developed. Diagnostic performance on intraoral images reached (84.6%) (C0), (90.6%) (C1), and (88.6%) (C2). When tested on simulated panoramic images, the model achieved (75.0%) (C0), (80.0%) (C1), (80.0%) (C2), with an overall accuracy of (78%). The results suggest that domain-specific transfer learning is a promising approach to build diagnostic models with limited datasets and reduced training time[25]. Faruk Oztekin et al. (2023) introduced an explainable deep learning model for the detection of dental caries using 562 panoramic radiograph images. The research evaluated three pre-trained convolutional neural network models: EfficientNetB0, DenseNet121, and ResNet50. The highest performing model, ResNet50, attained an accuracy of 92.00%, a sensitivity of 87.33%, and an F1-score of 91.61%.The model provides a promising and interpretable method for the early and reliable detection of caries [26].Divakaran and Vasanth (2023) conducted a study for the automatic classification of dental caries using (150) dental X-ray images. The Inception-based model was the best of the four models tested: ResNet, Deeper GoogLeNet, and Mini VGGNet. It had the highest accuracy (98%), making it highly suitable for clinical applications [27]. Mai Thi Giang Thanh et al. (2022) explored the use of deep learning for the detection of smooth surface dental caries through smartphone images. trained and tested four deep learning models (YOLOv3, Faster R-CNN, RetinaNet, and SSD) on a dataset of 1902 colored intraoral images taken with an iPhone 7 from 695 participants. The diagnosis of caries according to ICCMS guidelines. YOLOv3 had the best sensitivity for cavitated lesions at 87.4%, and Faster R-CNN had the lowest at 71.4%. while performance dropped for visually non-cavitated lesions (36.9% and 26%). Specificity exceeded (86%) for cavitated cases and (71%) for non-cavitated.These results indicate that smartphone-based AI systems may be beneficial for early dental screening[28]. However, photographic images captured by an intraoral camera or smartphone (RGB), having the advantage of convenience and safety, are currently used for the application of an artificial intelligence (AI) model to screen dental caries in many studies [29–33] and demonstrated significant improvements in performance with various techniques [34–35].

3. METHODOLOGY

This research aims to develop and evaluate a custom-designed Convolutional Neural Network (CNN) model for classifying RGB intraoral images into three diagnostic categories: normal teeth, early dental caries, and advanced dental caries. The proposed architecture, called as DentalNet-Lite, is a simplified and lightweight convolutional neural network derived from standard convolutional structures .It is not presented as a groundbreaking architectural innovation but rather as an enhanced, task-specific baseline model aimed at enhancing computing efficiency and diagnostic performance. DentalNet-Lite is built with the goal of balancing high classification accuracy and low computational complexity, making it suitable for deployment in both clinical and mobile settings. To benchmark its effectiveness, the model's performance is evaluated against five prominent pretrained CNN architectures: MobileNetV2, DenseNet121, ResNet50V2, Xception, and InceptionResNetV2, using transfer learning. Every model is trained and evaluated on the same intraoral dataset and assessed using standard performance metrics. This chapter details the dataset preparation, preprocessing steps, and data augmentation techniques, CNN architecture design, training parameters, and evaluation procedures that form the methodological framework of this research.

3.1 Dental Image Database

This research employed a publicly available and clinically confirmed dataset from the Mendeley Data platform [36]. The original collection comprises 2,000 RGB intraoral images, each illustrating an individual tooth. All images were classified into three diagnostic categories: healthy (normal), early dental caries, and advanced dental caries as shown in Figure 1. A qualified radiologist evaluated and improved the dataset to remove medically unnecessary or substandard samples, ensuring clinical relevance and quality. Subsequent to the curation procedure, a balanced selection of 1,200 images was chosen, with 400 images designated for each diagnostic category. Images were scaled to conform to the input specifications of the individual models for training purposes. The bespoke DentalNet-Lite model downsized images during training to conform to its architecture, whereas pretrained models preserved their original input resolution of 224×224 pixels to ensure architectural compatibility. As a result of these augmentation strategies, the total number of training images increased from the original 1,400 curated samples to 4,383 images, as illustrated in Figure 2, while maintaining equal class distribution across all three categories. With this expanded dataset, the images were split into 70% for training (3,727 images), 10% for validation (226 images), and 20% for testing (430 images).

Figure 1: Examples of the three diagnostic categories.

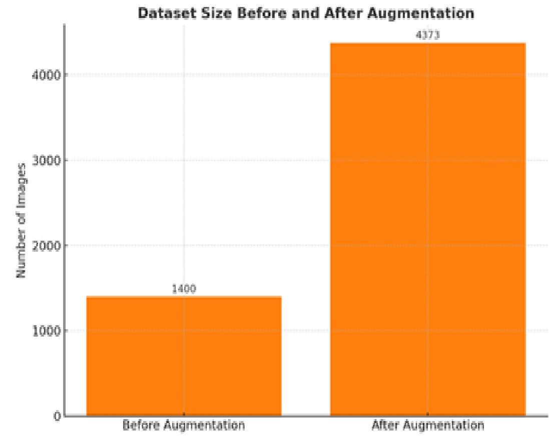


Figure 2: Dataset size before and after augmentation.

3.2 Architectural Design and Training Configuration of DentalNet-Lite.

This research aims to develop a lightweight and computationally efficient Convolutional Neural Network (CNN) model capable of effectively extracting clinically pertinent visual indicators associated with different stages of dental caries. The proposed model, DentalNet-Lite, was meticulously crafted and refined to achieve a balance of superior diagnostic performance, rendering it appropriate for deployment in both clinical and mobile environments. Table 1 depicts the architectural design of DentalNet-Lite. The model consists of three convolutional layers with increasing filter sizes (16, 3 and 64), each followed by max-pooling operations to diminish spatial dimensions while retaining essential information. A flattened layer converts the feature into a one-dimensional vector, succeeded by a dropout layer (rate = 0.5) to reduce overfitting. The classification consists of two dense layers, including a final softmax output layer with three units that denote the diagnostic categories: normal, early dental caries, and advanced dental caries. The model was implemented and trained using outlined in Table 2. Google Colab Pro was used as the development environment, employing an A100 GPU to enhance training efficiency. Python was the primary programming language, with Keras and TensorFlow serving as the main deep learning libraries. Key hyperparameters were selected based on empirical tuning to guarantee stable convergence and high generalization performance on the dental image dataset.

Table 1. Architecture of DentalNet-Lite

Layer	**Output Shape**	**Parameters**
Conv2D (16 filters)	(126, 126, 16)	448
MaxPooling2D	(63, 63, 16)	0
Conv2D (32 filters)	(61, 61, 32)	4,640
MaxPooling2D	(30, 30, 32)	0
Conv2D (64 filters)	(28, 28, 64)	18,496
Flatten	(50176)	0
Dropout (0.5)	(50176)	0
Dense (64 units)	(64)	3,211,328
Total params: Trainable params Non-trainable params:	3,235,107 3,235,107 0	(12.34MB) (12.34MB) (0.00 MB)

Table 2. Training environment and hyperparameter configuration

Soft/Hard	Information	Hyperparameters	Value
Prgm language	Python	Loss function	Categorical cross-entropy
Platform	Google Colab-pro	Optimizer	Adam
GPU	A100 GPU	Learning rate	0.001
RAM(System) RAM(GPU)	83.5GB 40.0 GB	Input size	128*128*3
Mostused packages	Keras Tensorfow	Epochs	250

3.3 Evaluation on Multiple Dataset Splits.

To ascertain the robustness and generalization capacity of the proposed DentalNet-Lite model, its performance was assessed using three train/validation/test splits: 80/10/10, 70/10/20, and 60/20/20. This experimental design aimed to examine whether the model maintains stable performance under varying proportions of training and testing data. ensuring that the only variable factor was the dataset partition ratio.

3.4 Pretrained CNN Architectures

- **MobileNetV2** Designed for mobile and embedded devices, Google developed a lightweight (CNN) architecture called MobileNetV2. It uses ReLU6 activations and 1×1 convolutions to reduce dimensionality through inverted residual blocks, which combine expansion and projection layers. It is highly efficient for low-power devices, with (3.5 million) parameters and (88) layers [37–38]. The main features of MobileNetV2 are minimal memory footprint and quick inference. The main limitations of MobileNetV2 are reduced precision on jobs involving fine-grained categorization

- **DenseNet121** belongs to the Dense Convolutional Network family, which rely on dense connectivity, every layer receives input from all preceding layers. This increases learning speed, mitigates vanishing gradients, and promotes feature reusing. It has (121) layers and some (8 million) parameters [39]. The main features of DenseNet121 are strong generalization, quick training, and good performance with limited medical datasets. The main Limitations of DenseNet121 are thick connections cause more memory consumption.

- **ResNet50V2** Using residual connections, ResNet50V2 is a revised form of the original ResNet that tackles the vanishing gradient issue. It reorders the internal block sequence such that Batch Norm → ReLU → Conv allows more consistent gradient flow in deep networks. Its (25.6) million parameter count accounts for (50) layers [40]. The main limitations of ResNet50V2 are Stable deep learning has advantages, including precise even on small datasets. The main limitations of ResNet50V2 are Slower inference and bigger model size are limitations.

- **Xception** Inspired by depthwise separable convolutions, Xception (Extreme Inception) is a more effective version of Inception. About (22.9) million parameters and (71) layers ,it achieves balance between complexity and efficiency. [41]. The main Limitations of Xception are lightweight, excellent precision for medical imaging classification. The main Limitations of Xception are Slower on low-end hardware; requires a modest dataset size.

- **InceptionResNetV2** InceptionResNetV2 combines the multi-branch design of Inception with residual connections from ResNet, making it one of the most accurate yet complex models. It consists of (164) layers and (56 million) parameters [42]. The main Limitations of InceptionResNetV2 are excels fine-grained image classification. The main Limitations of Inceptionresnetv2 are Not fit for mobile deployment, quite expensive computationally.

3.5 Comparative Analysis of CNN Architectures

A comparison analysis was performed to assess the architectural efficiency and scalability of the proposed DentalNet-Lite model against five known pretrained CNN models: MobileNetV2, DenseNet121, ResNet50V2, Xception, and InceptionResNetV2. The comparison evaluates essential structural characteristics, including the number of parameters (in millions), architectural depth (layer count), and computational complexity. The comparative results in Table 3 distinctly demonstrate that DentalNet-Lite attains a remarkably reduced parameter count and architectural depth compared to the pretrained models. Despite having only 8 layers and 3.2 million parameters, the model demonstrates exceptional classification accuracy and generalization. Its reduced computational complexity makes it highly suitable for real-time deployment in low-resource environments, such as mobile devices and rural clinics.

Table 3. Comparative summary of CNN architectures.

Model	Parameters (M)	Depth (Layers)	Computational Complexity
DentalNet-Lite	3.2	8	Very Low
MobileNetV2	3.5	88	Low
Dense Net121	8.0	121	Medium
ResNet50V2	25.6	50	High
Xception	22.9	71	Medium-High
Inception-ResNetV2	56.0	164	Very High

4. RESULTS and DISCUSSION

This section provides the quantitative evaluation and discussion of the proposed DentalNet-Lite model in comparison with five pretrained Convolutional Neural Network (CNN) architectures: MobileNetV2, DenseNet121, ResNet50V2, Xception, and InceptionResNetV2. All models were trained on an identical RGB intraoral dataset using uniform preprocessing, augmentation techniques, and evaluation metrics to guarantee equitable comparison. To prove the clinical significance of precise multiclass classification in dental diagnostics, four essential performance metrics were employed to evaluate the models: test accuracy, precision, recall, and F1-score.These metrics provide a comprehensive assessment of the models' ability to reliably detect caries and generalize to unseen clinical specimens.

4.1 Quantitative Performance Analysis

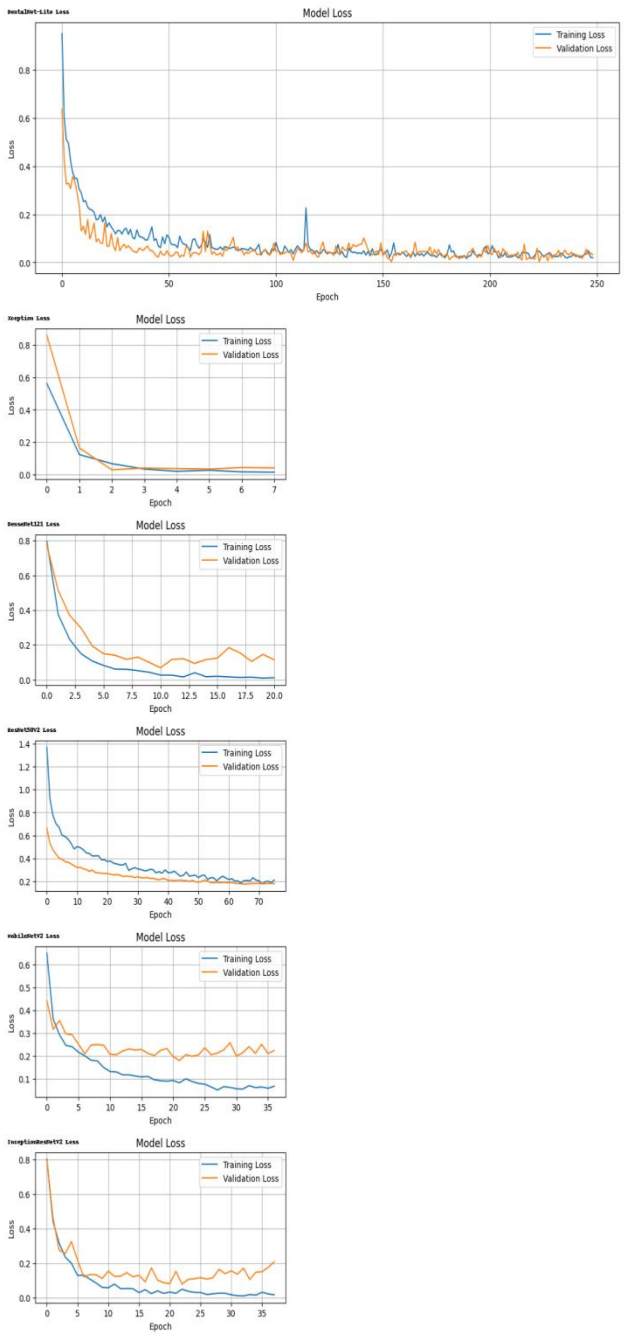
As shown, DentalNet-Lite achieved the highest test accuracy (99.07%) and F1-score among all models, despite having the fewest parameters (3.2 million) and only 8 layers. Table 4 displays the results of all models. In contrast, deeper models like InceptionResNetV2 and ResNet50V2 exhibited lower accuracy despite their increased complexity. Figures 3 and 4 depict the accuracy and loss Graphs during the training and validation phases for all models, enabling a thorough assessment of the training dynamics. Figure 3, Accuracy Comparison Across Models, illustrates that DentalNet-Lite and Xception consistently exhibited strong performance across all datasets, while InceptionResNetV2 demonstrated a decline in validation accuracy despite excellent training accuracy. Figure 4, Loss comparison among models, suggests that DentalNet-Lite and Xception maintained low loss values through training and validation, further demonstrating their robustness and a little overfitting.

4.2 Confusion Matrix and Error Analysis

To evaluate visually the classification performance of DentalNet-Lite, a confusion matrix is provided in Figure 5. Confusion Matrix of DentalNet-Lite Forecasts. The matrix shows that out of all 430 test samples, only 4 images were misclassified, all from the Early Dental Caries class, being predicted as Advanced Dental Caries. This supports the model's high recall and minimal false-positive rate for the other two classes. Figure 6, Examples of misclassified images. All four misclassified samples showed early lesions that appear severe in texture or lighting, leading the model to confuse them with more advanced Dental caries.

Table 4. Performance metrics of all CNN models.

Model	Test Accuracy	Precision	Recall	F1-score
Dental Net-Lite	0.9907	0.9907	0.9907	0.9907
Mobile NetV2	0.9625	0.9625	0.9625	0.9623
Dense Net 121	0.9708	0.9809	0.9708	0.9708
ResNet 50V2	0.9458	0.9465	0.9458	0.9460
Xception	0.9860	0.9863	0.9860	0.9860
Inception-ResNet V2	0.9708	0.9723	0.9708	0.9705



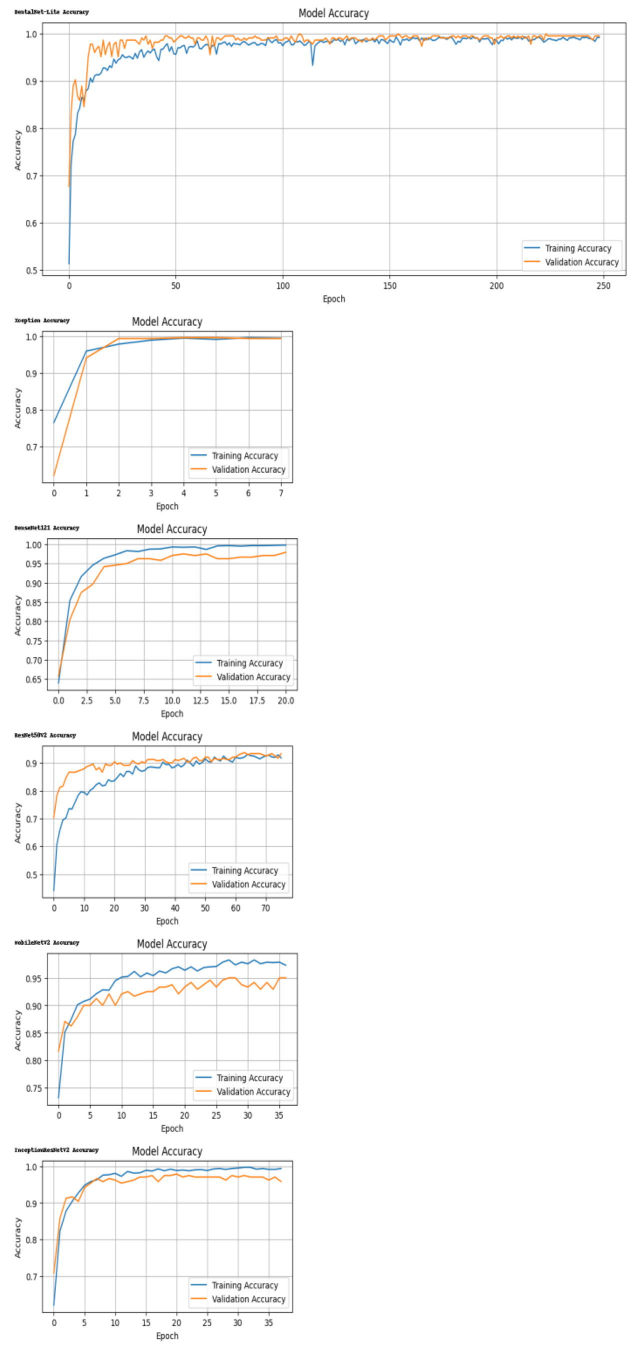


Figure. 3 Accuracy comparison across models

Figure. 4 Loss comparison across models

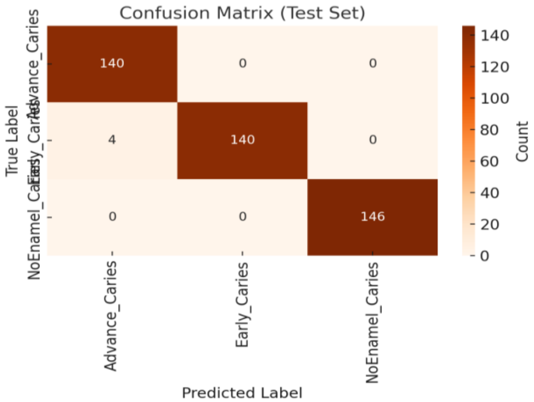


Figure. 5 Confusion matrix of DentalNet-Lite

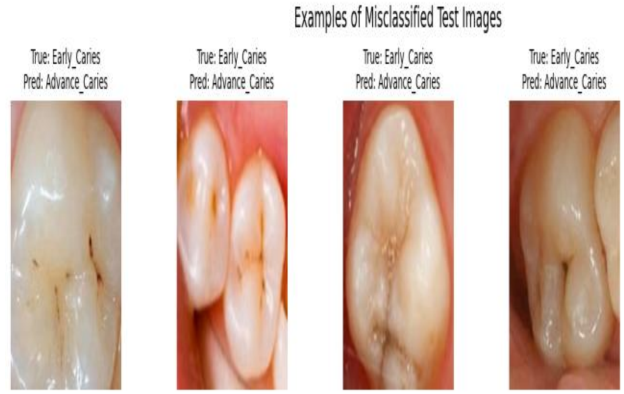


Figure. 6 Misclassified test samples

4.3 Performance Across Different Data Splits.

The table 5 displays the performance characteristics of the proposed model across three train/validation/test split configurations. The results indicate that DentalNet-Lite consistently attained remarkable performance, with test accuracy surpassing 99.5% in all cases. Notably, even when the training set size was reduced to 60% of the dataset, the model maintained a very high classification performance (99.50% accuracy, precision, recall, and F1-score), with a test loss of only 0.0136. suggesting its reliability for clinical application even under reduced training data scenarios.

Table 5. DentalNet-Lite performance across dataset splits

SplitRatio	**80/10/10**	**70/10/20**	**60/20/20**
Precision	0.9955	0.9907	0.9902
Recal	0.9954	0.9907	0.9901
F1-score	0.9954	0.9907	0.9901
Accuracy	0.9954	0.9907	0.9901
Loss	0.0259	0.0260	0.0136
Support	219	430	527

4.4 Confusion Matrix Analysis.

To appraise and analyze the classification performance of the proposed model, a confusion matrix was created to examine the distribution of true and false predictions across the three dental categories: Advanced dental caries, Early dental caries, and Normal tooth. Table 6 shows the calculated values of True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) for each category.

Definitions: Let the confusion matrix be denoted as M, where M[i][j] represents the number of samples with actual class i and predicted class j.

- True Positives (TP):

TP = M[i][i]

→ Correctly predicted samples of class i.

- False Negatives (FN):

FN = sum(M[i][j]) for all $j \neq i$

→ Samples of class i predicted as another class.

- False Positives (FP):

FP = sum(M[j][i]) for all j ≠ i

→ Samples of other classes incorrectly predicted as class i.

- True Negatives (TN):

TN = Total - TP - FP - FN

→ All correctly rejected samples not belonging to class i.

Application: These equations are applied per class in multi-class classification problems to evaluate model performance in more detail.

Table 6. False positives and negatives results

	Class	TP	FP	FN
1	Advanceddentalcaries	140	4	0
2	Early dental caries	140	0	4
3	Normal tooth	140	0	0

5. CONCLUSION

This study presented the development and assessment of a lightweight Convolutional Neural Network (CNN), called DentalNet-Lite, for the automated multiclass classification of dental caries using RGB intraoral images. The model, designed for simplicity and efficiency, was evaluated against five well-known pretrained architectures: MobileNetV2, DenseNet121, ResNet50V2, Xception, and InceptionResNetV2. The results of the research suggested that DentalNet-Lite outperformed all pretrained models in test accuracy, precision, recall, and F1-score, while possessing considerably fewer parameters and reduced architectural complexity. These results highlight the effectiveness of task-specific custom architectures in medical image analysis, particularly in scenarios where computational resources are limited. The research corroborates that lightweight models can serve as practical and dependable substitutes for deep, resource-demanding networks, particularly in real-time clinical applications, mobile diagnostics. The effectiveness of DentalNet-Lite demonstrates the potential of customized AI systems in improving intelligent dental diagnostics and enabling early intervention options.

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