JOURNAL OF EMERGING TECHNOLOGY AND DIGITAL TRANSFORMATION
ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME . 4 ISSUE . 2 (2025)

DEEP CONVOLUTIONAL NEURAL NETWORKS FOR CAVITY AND PIT DETECTION IN DENTAL IMAGES

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RECEIVED	ACCEPTED	PUBLISHED
08 June 2025	15 June 2025	29July 2025

ABSTRACT
If it is not addressed, several oral issues can arise from dental caries, one of the most prevalent oral disorders. However, access to professional dental care is often limited, particularly in underserved communities. Our proposed AI-based solution empowers individuals to monitor their oral health and detect early signs of cavities. Children are particularly susceptible to pits and caries in permanent molars, which mostly arise in the cavities on the occlusal, buccal, and palatal surfaces of molars. To address this challenge, we propose developing an AI-powered solution that utilizes smartphone cameras to capture and analyze dental images for cavity detection. This research enables image processing techniques and computer vision algorithms to identify and classify various cavities, including early-stage lesions and enamel defects. Using the Teeth Cave Convolutional Neural Network (CAVTee-CNN), which was particularly designed for dental cavity detection, we were able to minimize information loss during the preprocessing of images. This custom network was developed through extensive experimentation with convolutional layers, activation functions, and pooling mechanisms adapted to highlight dental features. The CAVTee-CNN Model enhances both efficiency and accuracy; it yields the best result of 85.2. By providing timely and accurate cavity detection, the application can empower users to make informed decisions about their oral health and seek appropriate dental care when necessary.

Keywords
Convolutional Neural Network, Deep learning, Image processing, Object detection, Teeth Cave Convolutional Neural Network (CAVTee-CNN), Preventive Fluoride Treatments

LINE ISSN
006-9726
NT ISSN
006-9718
VOLUME . 4 ISSUE . 2 (2025)

Introduction

Dental decay is a common dental illness that needs to be treated early to prevent more serious consequences. World Health Organization (WHO) estimates that dental problems affect over 3.5 billion people globally. Dental caries affects 530 million children's primary teeth. Due to its high cost, universal health coverage usually does not cover oral health treatment (UHC). In most wealthy countries, dental treatment makes up 20% of out-of-pocket medical expenses and an average of 5% of total health spending [1]. With the help of a teeth cavity detection system, dentists can easily organize and analyze dental images, from initial examination to diagnosis, as shown in Fig. 1. Dental platforms have shown a rapid increase in usage. For example, the number of dental images processed by the system substantially surged from a hundred thousand. Over the past ten years, machine learning and neural networks in particular have advanced significantly, outperforming humans on several tasks, including breast cancer diagnosis and the ImageNet image classification test [2]. Neural networks are also increasingly used in dentistry [3]. They have been utilized, among other things, to find dental cavities in pictures, periapical radiographs, bitewings, and orthopantomograms [4]. This technique can act as a second reader, offering a separate evaluation of the image and allowing dentists to double-check their choices. In addition to lowering the likelihood of caries being missed, the automated approach may be utilized to ascertain the location of caries for educational or dental documentation purposes [5].

An increase in the number of dental exams and more accurate diagnoses is likely to result from the system's ability to facilitate remote image analysis, which broadens the system's reach and visibility. Incorporating knowledge and experience, we investigate the circumstances in which dentists will use the online-posted image analysis, and we show that dentists' preferences differ [6]. When it comes to logistical and physical limitations, online dental image analysis has done away with proximity, preparation time, space, and a narrow target audience. However, there are a lot of new opportunities for errors in the digital age. Misinterpretation, promotion of incorrect diagnoses, and lack of accuracy are all examples of issues that can happen before, during, or after a diagnosis. Another kind of issue can happen when a dentist fails to interpret an image accurately [7]. The topic of much research has been the occurrence of errors before and after diagnoses. Modeling dentist behavior has been the primary focus of prior digital dental research. This study has concentrated on topics such as image analysis period, image attributes, motivation to diagnose, competitive advantage, and format. What drives dentists to use online image analysis has received less empirical attention in the aforementioned literature. Further research is advised, both empirical and theoretical, to clarify how dentists behave when diagnosing dental images. Accuracy, speed, and usability in the dental marketplace have all increased at an exponential rate. In the years to come, this tendency is anticipated to pick up speed [8]. An integral part of the dental marketplace, which makes use of image analysis techniques, is online image analysis mechanisms. Everyone from dental organizers to dentists and patients. The goal of the system is to keep user information secure, prevent errors, and keep the system up and running with little downtime.

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006-9726
NT ISSN
006-9718
VOLUME . 4 ISSUE . 2 (2025)

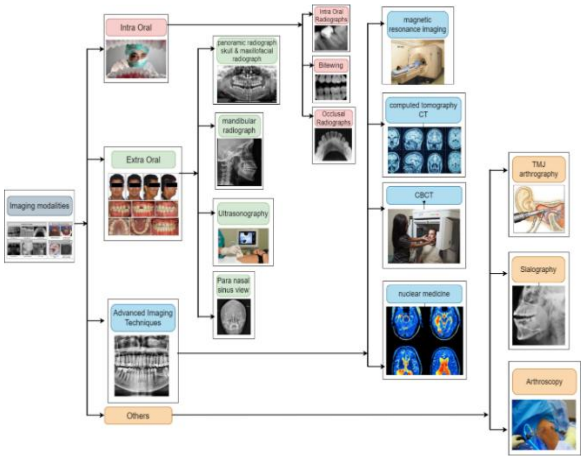

Fig 1. Dental imaging modalities

1.1 Intra Oral

In short, intraoral imaging equipment is used to capture radiography images that are viewable on a computer or tablet. To obtain radiography images, one must expose oneself to X-rays, a procedure known as direct optical imaging [9]. Intraoral imaging technology simplifies the process of capturing high-quality dental photos for patients and providing them with visual information in a timely and efficient manner. The parallel technique is the best exposure strategy for intraoral camera systems. A film is wrapped around the patient's teeth and positioned parallel to its axis in the parallel procedure.

1.2 Extra Oral

The films in these radiographs are positioned outside of the mouth cavity, and the beam is pointed in its direction. When there are clinically relevant lesions present, this type of radiography can be used to evaluate variations of the jaw, face bones, hard tissue growth, developmental anomalies, fractures, and the joint between the jaws [10].

1.3 CNN

It is an element of deep learning algorithms that are specifically designed for image analysis. This algorithm is capable of overfitting because it is a fully linked network that draws inspiration from nature. Nonetheless, one of CNN's main advantages is that this method needs minimum pre-processing [11].

2 Literature review

In the context of the medical field, patient health records are crucial [12]. The recorded medical information could serve as a guide for the physician in deciding on the best course of action and in providing the patient with timely, advanced treatment information to improve their health. Using an ineffective paper note system to frequently store medical data recording is a widespread best practice in Indonesia [13]. The lack of cavitations was more accurately diagnosed by CAVTee-CNN. Both diagnostic categories play a significant role in minimally invasive surgery. Children between the ages of seven and twelve should use pit and fissure sealants to keep their molars from developing cavities [14]. Dental caries, one of the oral health problems that affects about 3.5 billion people worldwide, must be examined by a dentist. By localizing and processing either colored photos or X-ray pictures captured by specialized dental photography cameras, the automated methods find and identify different regions from dental images [15]. According to the findings of China's fourth oral health epidemiological study (1), the country's caries rate for permanent teeth was 89.0% for those aged 35–44, 95.6% for those aged 55–64, and 98.0% for those aged 65–74 [16]. Because of its high metrics, YOLOv5 is suggested as a priority deep network for caries detection among those that have been studied [17]. Yolov5 with the bigger backbone and RetinaNET [18] with the SwimTransformer backbone were the top-performing designs. The comparison study is displayed in Table 1 below.

LINE ISSN
006-9726
NT ISSN
006-9718
VOLUME . 4 ISSUE . 2 (2025)

Table 1. Comparison study

Research Papers	Algorithm	Technology	Result
[19]	Deep learning algorithms used for caries detection.	Neural networks and AI-based techniques in dental imaging for caries detection.	It draws attention to the difficulties with data accessibility and model generalisation as well as the efficiency of deep learning in precisely identifying dental cavities.
[20]	(MPCA) with weight optimization using Non-Linear Programming. Feed-forward neural Network trained with Adaptive Dragonfly Algorithm (ADA).	Image Processing and Neural Networks.	It proposes a new method (MPCA-ADA) for caries detection and claims it might outperform existing methods.
[21]	It includes traditional image processing techniques and modern machine learning-based approaches.	Digital imaging (e.g., X-rays) and deep learning models	It highlights how well deep learning techniques work to increase dental caries detection efficiency and accuracy.
[22]	Visual inspection of teeth using codes of different lesion severities on various surfaces.	It relies on visual inspection only.	It enables dentists to detect and manage cavities more effectively by allowing early detection of non-cavity lesions.
[23]	It focuses on using a noise-filtering algorithm for detecting children's molars.	Noise reduction techniques in imaging to enhance.	It demonstrates improved accuracy in detecting children's molars

			by applying noise-filtering methods.
[24]	No Specific Algorithm was Mentioned.	Visual Inspection, Optical Techniques, Fluorescence, and laser light.	This research aimed to develop advanced diagnostic methods for early caries detection, meeting industry and clinician interests.
[25]	Segmentation using k-means clustering, feature Extraction, and selection classification using multiple classifiers	Digital Photography Image Processing Operations	The research presents a fully automated system for diagnosing occlusal caries using color photos captured via photography and aligns with the international caries detection and assessment systems (ICDAS II)
Our Proposed Method	A custom CNN model designed for the detection of cavities and pits	Deep Learning with Custom Image Dataset.	It Utilizes a combination of internet-sourced and self-captured images, labeled for training. Achieves an accuracy range of 85-90% in object recognition tasks, demonstrating robust performance.

3 Methodology

Researchers utilized a dataset of 3000 normal mobile images, divided into training and testing sets with a 20/30 ratio. They used the previously qualified Google Net Inception v3 CNN YOLO, R-CNN network for pre-processing and transfer learning. Various performance metrics such as precision, recall, specificity, positive and negative predictive values, AUC, and ROC were calculated. The dataset distribution based on maxillary and mandibular teeth and their diagnosis of dental caries was also analyzed. Images were resized to

416x416 pixels and converted to JPEG format. In the CAVTee-CNN model, we utilized the SGD Optimizer to maximize performance. The custom architecture, specifically designed with convolutional layers optimized for detecting cavities and pits, was meticulously trained over 15 epochs, with 32 batches per epoch and a learning rate of 0.01. Through strategic fine-tuning, we enhanced the model's focus and accuracy. As a result, the combined accuracy for premolar and molar datasets reached 82.0%, with an AUC of 0.845 for dental caries prediction.

3.1 Dataset

The teeth datasets from a typical ground data acquisition were collected for this investigation from several clinics, as well as from the teeth Robo-flow datasets. It includes graphics that depict cavities and non-cavities. The 3942 photos in the dataset were divided into 3468 images used for training and 154 images used for testing. The dataset snapshot is displayed in Fig. 2.

Fig 2. Snapshot of the utilized dataset

3.2 Image enhancement and preprocessing

The dataset included images in JPG format. For validation, 20% of the training set's images were used, along with a random horizontal flip. To zoom our model, a random zoom range of 0.2 was employed.

3.3 Justification

The CAVTee-CNN architecture was chosen specifically for its ability to meet the demands of caries detection, where speed, accuracy, and compact model size are essential. These factors are especially important for running efficiently on edge devices, which have limited resources for processing, filtering, and storing data.

To improve how information flows through the network, CAVTee-CNN uses a custom feature extraction method that boosts the way low-level features move through the layers. We've also implemented adaptive feature pooling, which helps carry important information from one layer to the next, improving the model's ability to accurately detect cavities, even when they're small or difficult to spot.

For detecting caries of different sizes, CAVTee-CNN generates feature maps at multiple scales, enabling the model to recognize small, medium, and large cavities with precision. This multi-scale detection capability allows CAVTee-CNN to handle the varying sizes of tooth decay effectively, making sure it can pick up on even the smallest features while maintaining accuracy across the board.

3.4 The deep convolutional neural network algorithm's architecture

10 layers make up the sequential model we have developed. Fig. 3 displays the model's architecture. The training dataset was subjected to 49 epochs and a learning rate of 0.001.

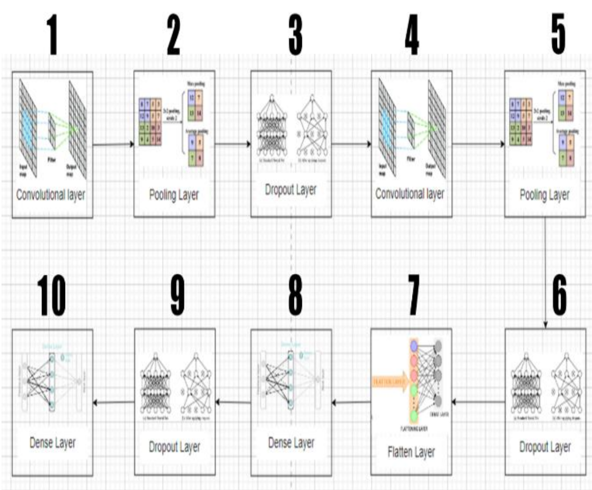

Fig 3. CNN model layers

LINE ISSN
006-9726
NT ISSN
006-9718
VOLUME . 4 ISSUE . 2 (2025)

Layer 1- uses a Conv2D layer with an input shape of (150, 150, 3) and "real" activation.
Layer 2- uses a pooling layer with a pool size of (2, 2).
Layer 3- uses a dropout layer with a value of 0.5.
Layer 4- A Conv2D layer with "real" activation is employed.
Layer 5- uses the pool size (2, 2) in the pooling layer.
Layer 6- uses a dropout layer with a value of 0.5.
Layer 7- To flatten the image into a 1-D array, utilize a flattened layer.
Layer 8- With 256 nodes and "real" as the activation function, a dense layer is employed.
Layer 9- uses a dropout layer with a value of 0.5.
Layer 10- uses a dense layer with the activation function "sigmoid."

4 Formulas/ Equations

The primary evaluation parameter that represents overall performance in the object detection job is mean Average Precision (mAP) [26]. We first determine the Precision and Recall for each category. Prediction accuracy is measured by precision, while performance in identifying all positives is shown by recall. The area under the associated Precision-Recall curve can be used to determine AP using the 11-point interpolation technique provided in the PASCAL VOC challenge. mAP is the mean value of APs in all categories. The average AP where the intersection over union (IoU), a positive threshold, is 0.5, is denoted as mAP@.5. With a step size of 0.05, mAP@.5:.95 represents the average AP for IoU between 0.5 and 0.95. The following formulas provide the mathematical definitions [26].

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

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

$$AP = \frac{1}{11} \sum_{recall \in [0,0.1,\ldots,1]} Precision(Recall)$$

$$IoU = \frac{area\ of\ overlap}{area\ of\ union}$$

$$mAP = \frac{1}{c} \sum_{i=1}^{c} AP_i$$

Where True Positive (TP), False Positive (FP), False Negative (FN), and categories (c) are the abbreviations listed.

5 Model Comparison

Table 2 shows the comparison of the existing model with the proposed models

ble 2. Comparison with different models

S.no	Model	Types	mAP@0.05	
1	YOLOv5 [27]	One-Stage	0.45	
2	EfficientDet [28]	One-Stage	0.52	0.40
3	RetinaNet [29]	One-Stage	0.50	0.37

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4	Faster R-CNN [30]	Two-Stage	0.42
5	Mask R-CNN [31]	Two-Stage	0.39
6	CAVTee-CNN	Custom CNN	0.65

6 Results and discussion

Our Proposed CNN model trained on a dataset of 3942 dental images (95% training, 5% testing) achieved good results in detecting caries for clear images as shown in Fig. 5. However, the model's accuracy suffered with blurry images within the dataset as shown in Figs 4,6, and 7. This suggests the need for further exploration of data augmentation techniques or alternative CNN architectures to improve robustness against image blur in dental caries detection.

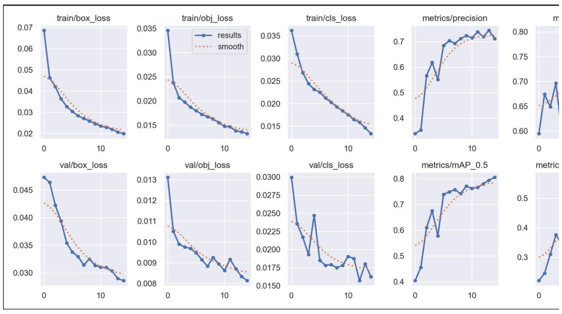

Fig 4. Training and validation losses

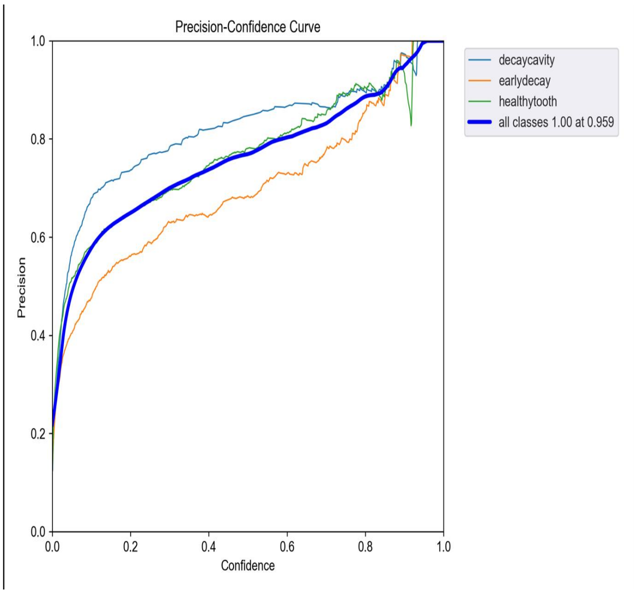

Fig 5. Precision-Confidence Curve for different classes

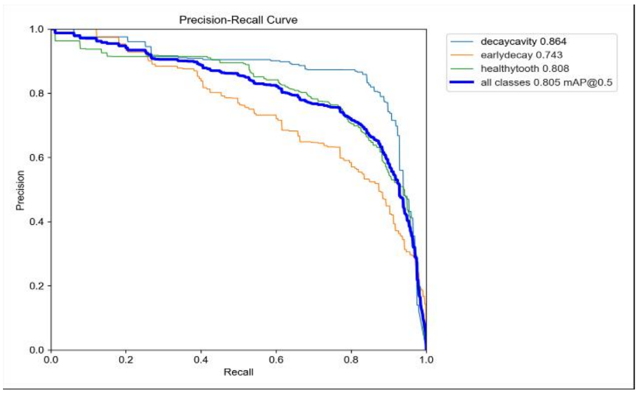

Fig 6. Precision-Recall Curve for each class

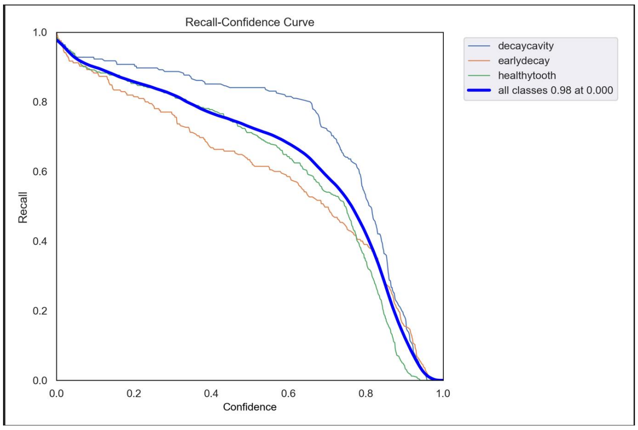

Fig 7. Recall-Confidence Curve for various classes

In this work, we created CAVTee-CNN, a unique convolutional neural network made especially for dental caries lesion detection and segmentation. Drawing inspiration from established CNN architectures, CAVTee-CNN integrates several advanced techniques, including dilated convolutions and a feature pyramid network, to enhance its ability to extract multi-scale features. These innovations were made to address unique challenges for dental image analysis.

Our comparative evaluation of CAVTee-CNN against traditional U-shaped networks, which are commonly used for similar segmentation tasks, underscores the effectiveness of our approach. The results indicate that CAVTee-CNN significantly improves the accuracy of caries detection and segmentation.

7 Conclusion

One of the best ways to prevent PFC, the hyper dental caries that affects children, is through PFS. Teenagers, too. A precise and ideal location can prevent children from missing the best time for PFS. In this study, we show how to use CAVTee-CNN, a proprietary deep learning network, to detect objects for PFS needs and dental caries in children's first permanent molars. We use an applet to distribute the pre-trained network to mobile devices. Our detection will aid in a home pre-screening for children's PFS needs and doesn't require complicated procedures or specialized dental equipment. Following training on the image data gathered using the applet, it is anticipated that the model's performance will continue to improve. Additional image data may aid in the investigation of methods for identifying small objects in low-resolution and dark photos.

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