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DENTAL CARIES SEVERITY DETECTION WITH A COMBINATION OF INTRAORAL IMAGES AND BITEWING RADIOGRAPHS

Jennifer[1]; Winni Setiawati[2]; Gabriella Adeline Halim[3]; Tony[4]

Department of Information Systems, Faculty of Information Technology[1, 2, 3, 4]
Tarumanagara University, West Jakarta, Indonesia[1, 2, 3, 4]
https://fti.untar.ac.id/[1, 2, 3, 4]
jennifer.825220040@stu.untar.ac.id[1*], winni.825220002@stu.untar.ac.id[2],
gabriella.825220050@stu.untar.ac.id[3], tony@fti.untar.ac.id[4*]

(*) Corresponding Author
(Responsible for the Quality of Paper Content)

Abstract— *Dental caries is a multifactorial oral disease caused by plaque due to bacterial sugar fermentation. Quite a number of dentists have misdiagnosed caries due to the subjective nature of visual examination and radiograph in early-stage lesions. Thus, research on the implementation of deep learning technology is expected to improve the accuracy of diagnosis. However, caries detection with deep learning has accuracy problems. This problem makes researchers interested in developing a deep learning method that combines Faster R-CNN algorithm and texture feature extraction to more accurately detect carious teeth from bitewing radiography datasets and intraoral images. The overall performance of the model to detect the radiographic class was slightly better than the intraoral class. Overall, the classification accuracy of the model was 88.95% which is better than previous research that only used one or the other type of images. GLCM (Gray-Level Co-Occurrence Matrix) is effective in detecting contrast areas, but it still cannot specifically distinguish normal anatomical contrast from caries. The Faster R-CNN model learned well and was able to differentiate between each caries type and was successfully integrated with the GLCM matrix for radiographic image pre-processing to facilitate caries detection. This approach could have the potential of assisting dental professionals in reducing diagnostic errors and increasing patient care.*

Keywords: *bitewing radiograph, caries, deep learning, intraoral image.*

Intisari— *Karies gigi adalah penyakit oral multifakorial disebabkan oleh plak akibat fermentasi gula bakteri. Cukup banyak dokter gigi yang melakukan kesalahan diagnosis karies akibat subjektivitas pemeriksaan visual dan radiografi pada lesi tingkat awal. Sehingga, penelitian mengenai implementasi teknologi deep learning diharapkan dapat meningkatkan keakuratan diagnosis. Akan tetapi, deteksi karies dengan deep learning memiliki masalah keakuratan. Masalah ini membuat peneliti tertarik untuk mengembangkan metode deep learning yang mengkombinasikan algoritma Faster R-CNN dan ekstraksi tekstur gambar untuk lebih akurat mendeteksi gigi karies dengan menggabungkan dataset radiografi bitewing dan citra intraoral. Kinerja keseluruhan model untuk mendeteksi kelas radiografi sedikit lebih baik dibandingkan kelas intraoral. Secara keseluruhan, akurasi klasifikasi dari model adalah 88,95% sehingga lebih baik daripada penelitian sebelumnya yang hanya menggunakan salah satu jenis citra. GLCM (Gray-Level Co-Occurrence Matrix) efektif dalam mendeteksi area kontras, namun masih belum dapat secara spesifik membedakan kontras anatomi normal dengan karies. Model Faster R-CNN telah belajar dengan baik dan dapat membedakan tiap tipe karies dan berhasil terintegrasi dengan matriks GLCM untuk pra-pemrosesan gambar radiografi, guna memudahkan deteksi bagian karies. Pendekatan ini dapat memiliki potensi untuk membantu tenaga Kesehatan gigi professional untuk mengurangi kesalahan diagnosis dan meningkatkan perawatan pasien.*

Kata Kunci: *radiografi bitewing, karies, deep learning, citra intraoral.*

INTRODUCTION

Dental caries is a multifactorial oral disease that is caused by plaque on dental hard tissues and then causes the bacteria in the biofilm to ferment sugars, produce acidic residual substances, cause demineralization which eventually become a cavity [1], [2]. Dental caries cases are commonly found in Indonesia, ranging from children to adults. The average prevalence of dental caries in the Indonesian population is 88.8% while the average prevalence of caries in permanent dentition in the world population is 28.7% with a total of 2 billion cases in 2019 [1], [3]. Despite technological advancements, traditional clinical dental examinations are still common occurences in everyday dental practices.

Caries treatment depends on the severity of each case from preventive measures, operative management [4], [5], [6]. Diagnostic examinations that are often used by consist of subjective, objective examinations and periapical and bitewing radiographs [5]. Misdiagnosis is when a disease is incorrectly identified due to lack of knowledge, experience, or malfunctioning tools, resulting in improper caries treatment. [7]. Not few dentists misdiagnose caries and other general pathological conditions. Unfortunately, relying on clinical examination solely has significant limitations with a previous study showing 31,1% of pedodontic patiens being misdiagnosed with this approach[8].

The deep learning notion of the Faster R-CNN (Faster Regional convoluted neural networks) method comes from a detection algorithm that combines regional proposals with convolutional neural networks and uses region proposal networks (RPN). It could use its neural networks to learn strategies in order to make their own regional proposals for faster detection [9]. The integration of deep learning technology with Faster R-CNN method— an algorithm that can learn image data – is performed to obtain patterns and characteristics. [10], [11], [12], [13]. Due to this fact, deep learning is particularly suitable for finding carious pattern in intraoral clinical examinations and radiographic support and improve the accuracy of caries detection.

Research [13] shown that Faster R-CNN outperformed YOLO in caries detection accuracy through intraoral images. Despite YOLO's real-time detection capabilities making it more suitable for applications requiring immediate results, though it struggles with subtle dental features. For another deep learning study conducted by [14] used bitewing radiographs for caries detection. The study applied U-Net, a type of CNN, to significantly so that the accuracy of caries detection. U-Net has significantly higher accuracy than that of dentists due to its ability of segmenting image pixel-wise creating higher precision, yet it is also a very complex model with an overdependence of data annotation in order to a very high chance of false positive happening. These differences highlight Faster R-CNN as the best model chosen for this research.

AI assisted analysis in the medical field is also very limited as the technology continues to evolve. Caries detection with AI has problems including the need of external validation for clinical result reliability, the possibility of error in manual training data annotations by dentists, and subquality available image data for deep learning analysis [14], [15]. These problems will hinder the model's ability to learn caries pattern and features for real clinical applications.

This problem has drawn researchers to develop an AI methods that combine bitewing radiograph and intraoral images to more accurately detect carious teeth. The combination of those images are expected to increase the accuracy of diagnosis due to the fact that radiographs can detect hidden carious lesions [16], [17]. This notion of combining traditional and novel methods to increase accuracy in diagnosis has been done before but has never been implemented for previous deep learning research as they primarily focused on single image modality [18], [19]. This research also emphasizes on minimizing the gap that often occurs in caries detection, by combining Faster R-CNN as a caries detector with GLCM (Gray-Level Co-Occurrence Matrix) which analyzes the difference in texture and intensity of caries-affected and non-caries-affected areas in radiographic images, resulting in accurate detection on both types of data. With this approach, it is expected to overcome low accuracy and difficulty in processing of different types of data. With this approach, it is expected to overcome low accuracy and difficulty in processing of different types of data, as illustrated in Figure 1.

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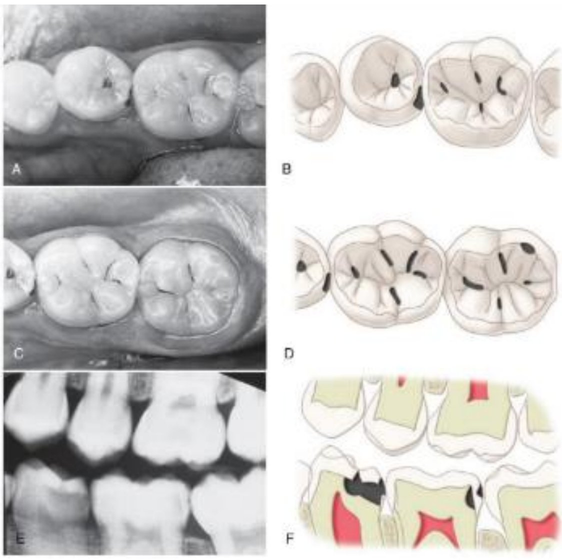
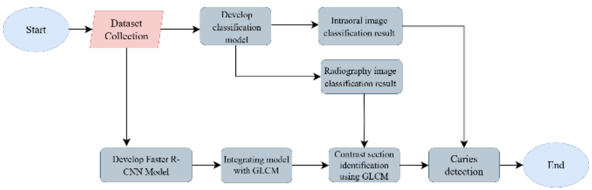


Source: (Ritter et al., 2019)
Figure 1. Intraoral Photographs Of Patient's Teeth With Extensive Caries In Molars And Bitewing Radiographs And 2D Illustrations

MATERIALS AND METHODS

Caries detection via Faster R-CNN can be achieved by training algorithm using a dataset of dental intraoral images and radiographs. As illustrated in Figure 2, datasets are preprocessed using augmentation, size adjustment, and normalization. The training dataset is separated into 3 parts, namely severe caries teeth, moderate caries and non-caries consisting of a mixture of intraoral and radiographic images. The prediction process uses a randomly selected testing dataset.



Source: (Research Results, 2024)
Figure 2. Research Flow Diagram

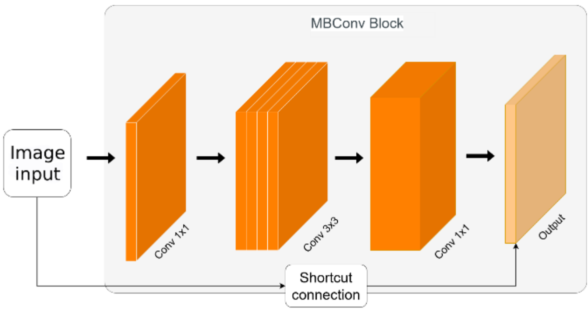
Data Collection

This study uses the Caries-Spectra dataset which represents intraoral caries images and Dental caries in bitewing radiographs [20], [21]. Both image datasets are utilized because they are common imaging used for coronal dan interproximal caries detection. The Caries-Spectra dataset consists of 520 images which are divided into 173 images into severe caries, 173 images for moderate caries, and 173 images for non-carious teeth with dimensions of 224x224 pixels. Meanwhile, the radiographic image consists of 511 images that have been augmented by rotating, flipping, and mirroring the images. The datasets consists of intraoral and radiography images, collected with an equal distribution of 50% for each type of image. The total number of collected images was then splitted into training and validation sets with ratio of 80:20. The performance of classification model evaluated with a confusion matrix which provides detailed breakdown of the model's predictions by showing the precision, recall and F1 Score of each class. This model aim to focus on recall as much as possible, since it is important to avoid false negatives, which could overlooking relevant images. Misclassification of intraoral images could result in missing vital informations.

The bitewing intraoral and radiographic images have undergone resizing to homogenize the dimensions to 640x480 pixels.

Image Type Classification with MobileNetV2

Before the datasets are merged, they are classified through a pre-trained MobileNetV2 model. This model uses the Mobile Inverted Bottleneck (MBConv) layer, which is a combination of depth-wise separable convolutions and inverted residual blocks.



Source: (Research Results, 2024)
Figure 3. MobileNetV2 Architecture

Figure 3 shows the architecture of MobileNetV2 with the Mobile Inverted Bottleneck (MBConv) block. The main consideration in using MobileNetV2 is because this model is designed to reduce the computational burden compared to a conventional Convolutional Neural Network (CNN). MobileNetV2 utilizes inverted residual blocks that combine depth-wise separable convolutions and inverted residual blocks for higher computational efficiency [22]. In addition, the shortcut connections in this architecture aim to improve the ability of gradients to spread more effectively across the network layers thus improving the overall efficiency and performance of the model [23].

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Feature Extraction of Bitewing Radiographs With GLCM

Feature extraction is the process of analyzing the texture of an image. Gray-Level Co-Occurrence Matrix (GLCM) is one method to extract texture features from images by measuring the frequency of pixel pairs that appear at a spatial distance with a certain intensity value [24]. The frequency of occurrence of a pixel intensity pair in the image will be included in the co-occurrence matrix. This matrix generates the probability of occurrence by normalizing the matrix elements and total pixel pairs. This research focuses on using contrast features to see the caries section based on how contrasted/different an image is in a certain area by measuring the local intensity between pixels and their neighbors. The contrast calculation in GLCM is shown in equation (1)

$$Contrast = \sum_{i,j=0}^{N-1} P(i-j)^2 \qquad (1)$$

P (i, j) denotes an element of the GLCM that represents the probability of occurrence of a pair of pixels with intensities i and j. N represents the number of gray levels in the image, while i and j are the contrasting pixel intensities. Contrast will be 0 if the neighboring pixels (i and j) have the same value. Thus, the greater the difference between the values of i and j, the greater the contribution to the contrast value. In this processing, the parameters used are distances of 5 pixels and angle 0 to account for horizontally adjacent pairs. These parameters were considered to capture broad patterns that commonly found in teeth affected by caries. Datasets that have been classified and detected as radiographs will be extracted in GLCM to identify parts of the tooth that have contrast with other parts, so that they can be the first step in caries detection.

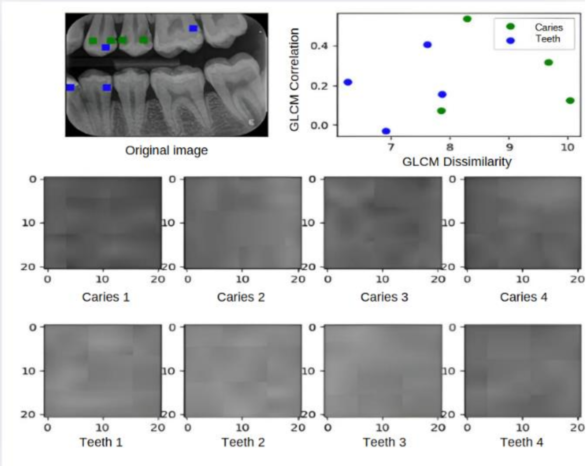
Some of the steps that need to be done before analyzing the contrast level using GLCM are described as follows:

1. Image Preprocessing

Less than ideal contrast in bitewing radiographic images can sometimes alter the opacity of anatomical structures, resulting in an unclear interpretation of the thickness of structures, both in the background and foreground, to the naked eye [25]. Thus, histogram equalization techniques are used with the aim of improving the global contrast of the image by flattening the pixel intensity distribution in intraoral radiographic images such as bitewing [26]. This process is useful to clarify the intensity variations between pixels in order to facilitate the process of identifying textures and patterns in the image.

2. Dark Area Segmentation

The segmentation method of inverted binary thresholding operation is used to isolate the dark areas in the image. Thresholding is an intensity-based segmentation method, where pixels with intensity below a threshold of 50 will be converted to white (255), while other areas become black. We used this method for highlighting dark areas that may indicate caries.



Source: (Research Results, 2024)

Figure 4. Segmenting Caries and Non-Carious Features

Figure 4 shows the healthy part of the tooth is shown with a blue patch, while the green patch represents the carious part of the tooth. In the GLCM dissimialirity graph, it can be seen that there are differences in feature characteristics between healthy teeth and carious teeth, as the patches of healthy teeth and carious teeth show characteristics that tend to be light and dark, respectively.

3. Image Segmentation and Analysis In Patches

This stage divides the image into small patches/sections that allow analysis of small areas of the image. This approach is useful for caries detection that does not affect the entire image.

The contrast that has been computed using GLCM on each image is analyzed to determine how contrasted each patch is compared to its neighbors, which is useful for identifying areas with signs of caries texture changes. The patch size of 32x32 is selected in this method to ensure a balance between capturing sufficiently small local details and perserving global patterns. This size is optimal for

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detecting subtle texture cariations associated with caries while maintaining computational efficiency and image context integrity.

Caries Severity Detection with Faster R-CNN

The main advantage of using Faster R-CNN is the addition of the Regional Proposal Network (RPN), a network that generates candidate boxes (anchor boxes) based on the anchor mechanism before extracting features. The selection of candidate boxes will generate a score that indicates the likelihood of an object [13]. RoI pooling will resize the generated scores to a fixed size to predict the class and perform bounding box regression. Bounding boxes will then undergo regression (refinement) to produce coordinates that are closest to the ground truth boxes [13], [27]. Bounding boxes that still overlap will go through a filtering process with Non-Maximum Supression and leave the bounding box with the highest score for each object.

RESULTS AND DISCUSSION

The pre-trained MobileNetV2 model is able to classify the types of bitewing radiographic images and intraoral images well. Radiographic images are represented by label 1 while intraoral images are represented by 0. The classified images will be retrained in the Faster R-CNN model to obtain a prediction of the part of the tooth that has caries based on its severity.

MobileNetV2 Model Performance

The best model performance was obtained by setting the hyperparameters as batches of 4, epochs of 10, threshold 0.5, learning rate 0.001, and using the Adam optimizer. The precision, recall and f1 score values for intraoral images detected by the model are 0.83, 0.52, and 0.64, respectively. While for radiographic images 0.66, 0.90, and 0.76 with an overall classification accuracy of 71.05%. Table 1 summarizes the performance of the model.

Table 1. MobileNetV2 Model Accuracy

Class	Precision	Recall	F1 Score	Accuracy
Intraoral	1.00	0.79	0.88	88,95%
Radiography	0.81	1.00	0.90	

Source: (Research Results, 2024)

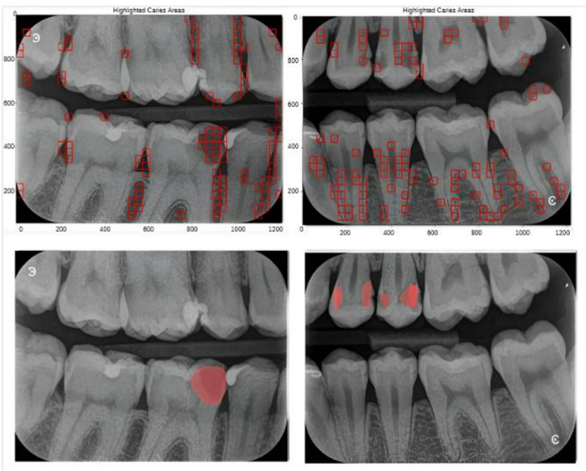
The table shows that the precision of the intraoral class reaches 100%, where the model is able to predict with 100% correctness within the intraoral class, but only 79% of the intraoral images can be detected by the model. However, the f1 score of 88% for the intraoral class shows a good balance between precision and recall.

The radiographic class, on the other hand, had a lower precision than the intraoral class (81%) but 100% of the radiographic images could be detected, with a higher f1 score (90%), the overall performance of the model to detect the radiographic class was slightly better than the intraoral class. Overall, the classification accuracy of the model was 88.95% which is better than previous research that only used one of the other type of images. Caries detection on an intraoral image using YOLO V3 and Faster R-CNN have 75% and 80% accuracies respectively while caries detection using radiograph has a 78,95% accuracy[11], [13] .

Contrast Identification in Bitewing Radiographs With GLCM

The classification results by the MobileNetV2 model showing bitewing radiographs were then processed using the GLCM matrix. Next, the image is segmented into sections or patches that go through a segmentation process to determine the dark areas. In the dark area segmentation process, a threshold of 40 is set to isolate dark objects in the background. Meanwhile, a threshold of 90 is set in the process of determining the carious area to take the highest 10% value that is most different from other areas in the image.

Parts of the image that were identified as having high or significant contrast were marked with a red box of 32x32 pixels. This helps to highlight specific areas of the image that may require further attention in diagnosis.



Source: (Research Results, 2024)
Figure 5. Contrast Area Identification Results

The threshold set in dark area segmentation and the patch size in image processing have a

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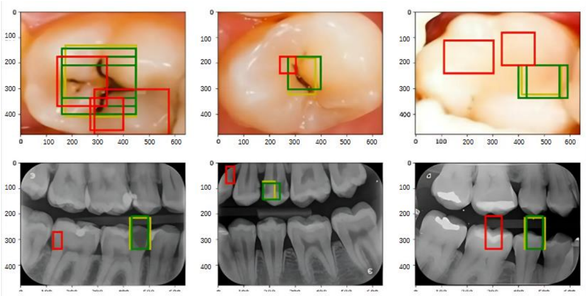
significant impact on the analysis results. A large patch will result in a large detection area, and vice versa. A high threshold will capture parts of the radiograph that have little contrast with other parts. However, in order to not detect unnecessary contrast areas are in the analysis, this study uses a threshold of 90 so that the contrast area suspected of being caries can be maximally captured.

The contrast area on the bitewing radiograph is shown in the set of red boxes in Figure 5. In this area, there is a healthy part of the tooth, such as the pulp, which is identified as a contrast area. However, Figure 5 shows the areas where the presence of dental caries has been successfully identified using GLCM calculation. The suspected area of dental caries is marked with a pink mark. This shows that GLCM is effective in detecting contrast areas, but it is still unable to specifically distinguish between contrast caused by caries and contrast originating from other healthy tooth structures.

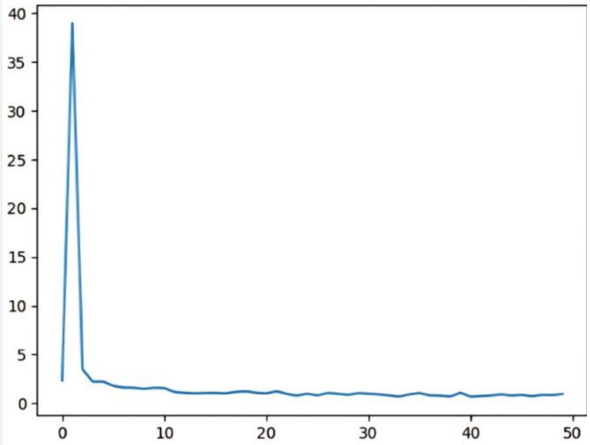
Carious Tooth Detection with Faster R-CNN

The contrast parts that have been generated by GLCM are forwarded during the annotation process to determine the ground truth boxes in the sample data. The images consist of 3 intraoral images and 3 bitewing radiographs, each image represents a level of severity of caries consisting of advanced enamel caries, early-stage enamel caries, and non caries.



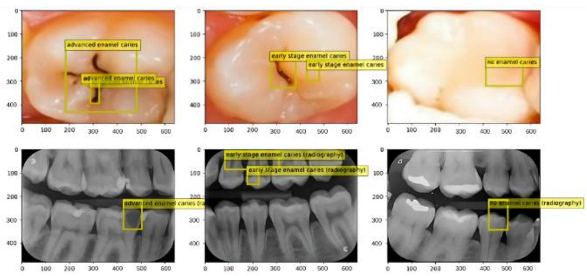
Source: (Research Results, 2024)
Figure 6. Prediction Result With Ground Truth Boxes

Predictions by the model are indicated by positive anchors, which are predictions that are considered correct because they are closest and overlap with the ground truth boxes marked with green boxes, while negative anchors, which are predictions used by the model to distinguish objects from the background or irrelevant objects, are marked with red boxes. The ground truth boxes are marked with yellow color which shows the actual object. Based on Figure 6, the model can predict objects close to the ground truth boxes.



Source: (Research Results, 2024)
Figure 7. Loss Function Graphic

After the training process is carried out, the loss of the model prediction is visualized with a graph showing the loss function in Figure 7. Loss is a result that should exist but is not captured/detected by the model in the training process, causing a lack of accuracy. It can be seen that there is an increase at the beginning of the training process but gradually decreases when the epoch reaches 20, which reflects that the accuracy of the model is sufficient with minimal loss.



Source: (Reserach Results, 2024)
Figure 8. Overall Prediction Results

Prediction with Faster R-CNN resulted in several frames listed as in Figure 8. The object successfully detected several possible caries in radiographic images with the category “moderate caries”, where the ground truth boxes initially targeted only one suspected carious section. This shows that the model has learned well and can distinguish each type of caries and successfully integrated with the GLCM matrix for pre-processing radiographic images, to facilitate the detection of caries. The findings of using 2 different image datasets might suggest an integration between

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traditional caries diagnostic procedures with this method of deep learning model to reduce diagnostic errors and increase patient care. Ultimately, it will assist dentists and improve treatment planning.

CONCLUSION

This research was conducted with the aim of detecting the severity of dental caries using two types of images —intraoral images and bitewing radiographs —using the Faster R-CNN deep learning model through the classification process using the MobileNETV2 model. The conclusions of this study show that combining two different image datasets enabled the MobileNetV2 model to achieve a high overall classification accuracy of 88.95%. The Faster R-CNN model is able to integrate with the GLCM matrix for bitewing radiographic image processing with the aim of identifying contrast parts. Lastly, The model can also predict caries severity from severe, moderate, and non-caries. This approach has the potential to reduce diagnostic errors and increase patient care by dental professionals.

This study has certain limitations. The accuracy of the model could be improved with larger and more diverse datasets or higher-quality images. Future research could explore other CNN pretrained models that have more accurate classification and detection capabilities.

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