Detecting Dental Caries Using Oral Imagery Based on Deep Learning Algorithms: A Systematic Review

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Abstract. Oral diseases such as dental caries are distressing health problems that affect people throughout their lifetime and they require early diagnosis to avoid extreme measures and expenditure. With development in the application of Artificial Intelligence, Deep Learning (DL) has evaloved as a potential technology in dental diagnosis bringing about efficiency, precision and reproducibility in caries diagnosis. DL models such as Convolutional Neural Networks (CNNs), these techniques show outstanding performance in distinguishing carious tissue and its extent, detecting and mapping carious lesions across different imaging techniques. However, there are some challenges in this field, namely the dependency on high-quality annotated data, the susceptibility to variability of images, and problems with early and secondary caries identification. The current review aims at categorising the existing literature and comparing the DL-based methods for detecting dental caries and identifies the key research gaps. This review determines the existing methodologies and their usage in detail while discussing the challenges. This research helps researchers to understand the state-of-the-art DL models and discuss future directions for concerning issues like dataset variety, model transferability, and their implementation into clinical practices. To increase the effectiveness and accessibility of the current dental diagnostic instruments, it is believed that the results of this study would pave the way for future technological developments in this field.

Keywords: Artificial Intelligence, Convolutional Neural Networks, Deep Learning, Dental Caries Detection, Oral Imagery.

1 Introduction

Dental caries, which are also known as cavities, are one of the main concerns that the world has to deal with and they are affecting not only old people but also many children and adults. Cavities are caused mainly by the gradual loss of minerals from the tissues of the teeth due to the acid that is produced by the bacteria when they break down carbohydrates in our diet [1]. The early sign of dental caries is crucial to discover so as to address the problem before it progresses to such an advanced stage that it has to be treated by highly invasive methods like root canal therapy or tooth extraction, both of which are very costly and require a long time to heal [2, 3]. The traditional methods of caries detection are such as visual-tactile examination and radiography, which are resource-intensive and are not stable based on examiner expertise. Therefore, the need for more efficient diagnostic solutions has arisen [4]. Gadgets that come from technologies have shown the use of intraoral and smartphone cameras for taking the photographic images of the teeth, which is a non-invasive and low-cost method of screening. The images are then used as the data for AI and DL algorithms, which due to the capacity of

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the latter to carry out the functions automatic, reliable, and standardized diagnosis, are considered the best methods for detecting caries [5, 6].

CNNs, which can be U-Net and Faster Region based CNN (R-CNN), have been used for various kind of work, like segmenting, classifying, and localizing carious lesions on tooth surfaces. This way the machines can see more clearly by looking only at the relevant tooth areas in the images, thus improving their detection accuracy and reducing false positives [7]. Nevertheless, the new findings notwithstanding, the currently existing deep learning models have some challenges. Challenges, such as the decreased capability in recognizing noisy, altered, or crowded settings; and additional caries-related anomalies like discoloration or crowns, have been presented in the case [8]. The bottleneck of the models' generalizability, indeed, the diversity/size of datasets used in experiments that do not cohere with variability in clinical settings are the factors causing this problem. Work undertaken in the future aiming at the incorporation of the multisite dataset, the application of the advanced data augmentation technique to the manifold exposure of the real world, and the optimization of the model that more directly distinct between the carious and the non-caries lesions should be developed [9, 10].

The structure of the manuscript is arranged as follows: literature survey in section 2, taxonomy of DL approaches in section 3, comparison of various DL methods in dental caries detection in section 4, ongoing challenges discussed in section 5 and the overall summary in section 6.

2 Literature Survey

Zhang, X et al. [11] suggested a DL framework for analysis of oral photographs to overcome the drawbacks of the traditional caries screening approaches. Automated image analysis was performed by using the CNNs that have higher reliability than the conventional methods. The experiments resulted in the enhanced diagnostic precision and neutrality and indicated the application of this approach to global screening methods. However, the drawbacks of this research are data dependency on high quality image and a large number of labeled training data that hinders the application in different clinical fields. Park, E.Y et al. [12] presented the novel CNN based segmentation technique for increasing the capacity of detecting caries. Both segmentations based on U-Net and lesion detection based on Faster R-CNN have been implemented. All models achieved good levels of sensitivity and great levels of precision over base models according to evaluations. However, some of the limitations include the fact that it utilized only professional grade intraoral images, further usage of the method may not be feasible in the developing the real-world applications. Kühnisch, J. et al. [13] developed a new diagnostic system that utilized CNN for diagnosis using intraoral photographs. The research proved that machine-based evaluation can be as accurate as specialist doctors and show certain diagnostic results. Although it provided an effective solution to the problem of inter-examiner variability, the method showed difference in performance in classifying the borderline lesions and need to be improved in order to address the real-world issues. Lian, L et al. [14] suggested a framework to explore the efficiency of nnU-Net and DenseNet121 when diagnosing dental caries and differentiating between healthy and diseased areas of the teeth on panoramic radiographs. Both models presented similar accuracy, which brings the possibility of automation into diagnostic pathway. Drawbacks of this research highlights the limited dataset and difficulties in accommodating the variability in radiograph image quality that requires the enhancement of the method for improved versatility.

Liu, Y. et al. [15] presented a research for classifying linked teeth as oral-mamba. A new approach was introduced for diagnosing dental calculus, caries, and gingivitis from intraoral images. It was seen that the model surpassed the conventional approaches such as U-Net in terms of results. However, there is a problem of generalizability along with the need for consistent, high-quality images of the area of interest. Van Nistelrooij et al. [16] focused on creating an algorithm using a CNN network with a Swin Transformer backbone for detecting and classifying secondary caries from bitewing radiographs. It presented high specificity for the identification of the lesion; however, it could present modest sensitivity to the same. The research also showed other challenges that include optimising for first-instance lesions and adapting the approach for use in a standard clinical setting. Makarim, A.F et al. [17] presented an approach of comparing several AI models such as You Only Look Once (YOLOv5) and MobileNet V2 for classifying dental conditions from the intraoral images. However, in terms of accuracy and speed, YOLOv5 performed better than other models; dataset, the issue of imbalance in most cases, and sometimes the model's inability to detect them. This shows the need of focus on broaden datasets and enhancement of generalization abilities. Zhang, R. et al. [18] developed a novel method based on SegFormer, a deep learning model for the semantic segmentation of lesions of oral mucosal diseases. Using an advanced multi-scale feature fusion and ViT-base architecture, the study focused to overcome the existing models' issues, for instance, U-net and DeepLabV3, in segmenting the lesion boundary. Results showed that the SegFormer had better segmentation accuracy. However, the study pointed out some of the challenges that include; high computational power required to implement and the reliance on massive annotated databases to make the predictions, two of which could pose a hindrance when the aims are to be realized in resource constrained environments.

Park, E.Y et al. [19] focused on evaluating the performance of CNNs in classifying caries based on Quantitative Light-induced Fluorescence (QLF) images which enhanced the intraoral structures by displaying both demineralized enamel and cariogenic bacteria through autofluorescence. The Xception model was used with a intraoral QLF images. The results indicated increased accuracy, precision especially when classifying masked images, and sensitivity to change in accuracy. Some disadvantages include a small quantity of samples for some types of caries, and few samples with anterior teeth and smooth surface caries. Tan, R et al. [20] introduced a handheld device with CNN for the evaluation of the QLF images. The study focused on addressing the limitations of the traditional caries detection methodologies. CNN was used as a core model in the intraoral images for caries lesion detection and staging was done using YOLOv5. The evaluation showed acceptable sensitivity and specificity, mainly with reference to the detection of extra-occlusal caries. However, it needs QLF imaging which has lower efficacy for proximal caries detection and also show positive response from extraneous stains. Furthermore, image labels used clinical observations in their creation and not pathologic data, which hindered model accuracy.

2.1 Taxonomy of Deep Learning Approaches for Dental Caries Detection

The taxonomy, in this section, represents the classification of various DL approaches for dental caries detection. The DL approaches are classified into various models such as object detection models, segmentation models, classification models, and transfer learning models. The detailed structure of the taxonomy is represented in fig 1 and further explained in the sections below.

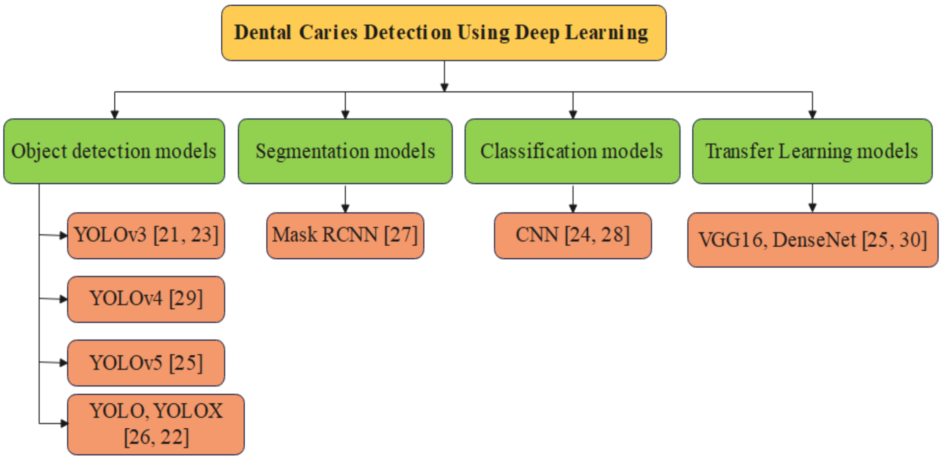

Fig. 1. Taxonomy for Dental caries detection using Deep Learning.

2.1 Object Detection Models

Thanh, M.T.G. et al. [21] focused on detecting dental caries, especially cavitated and non-cavitated lesions, using Deep Neural Networks (DNN), YOLOv3, Faster R-CNN, and RetinaNet, using intraoral images captured by a smartphone. The imaging modality used involved 1902 images annotated. For improving the model resistivity, measures of data augmentation were employed. The accuracy demonstrated by YOLOv3 was higher when detecting cavitated caries with sensitivity of 87.4%, and specificity higher than 86%. However, the method provided a low sensitivity for classifying non-cavitated lesions only and, therefore, shed light on the issues surrounding non-invasive imaging for early stages of caries.

Xiong, Y. et al. [22] presented a ToothNet, as a modified YOLOX practitioner for the joint detection of dental caries and fissure sealants in intraoral images. To create the dataset, 1,020 images were annotated with signals from three experienced endodontists. The model was tested with AUC of 0.925 for caries and 0.902 on sealants, sensitivity of 0.807, and precision of 0.814. As a result of its ability to perform multiple tasks simultaneously, ToothNet has substantial diagnostic potential, although its use of confidence thresholds and the quality of the dataset restricts it in clinic.

Ding, B et al. [23] suggested a framework to detect primary and secondary caries using YOLOv3 algorithm with augmented data of the intraoral images. The large dataset of 7,980 images enhanced generalization and yielded primary carity mAP of 85.48%, precision of 93.33 % and recall of 69.42%. Although the approach has high accuracy in the primary caries, its efficiency is limited for the detection of the secondary caries due to lower recall and problems connected with non-homogeneous conditions of the image.

Tareq, A et al. [25] presented the fused YOLO model incorporating transfer learning such as VGG16 and DenseNet to detect dental cavitations from unstandardized smartphone images. An experiment was performed on an augmented dataset of 1,703 images with a diagnostic accuracy of 86.96%, precision of 89%, and recall of 88%. The approach has flexibility in handling non-standardised images favorable for remote diagnosis; however, it requires high quality images with similar performance in different areas of clinical practice.

Bayraktar, Y et al. [26] suggested the use of modified YOLO for interproximal caries detection, and applied on the images of the radiographs of which 1000 were annotated. The accuracy observed was 94.59%, sensitivity 72.26%, specificity 98.19%, indicating the effectiveness of the model in clinical practice. The model has good accuracy in general, yet a relatively low sensitivity regarding molar caries suggesting the improvement for better identification of caries in these areas.

Farook, T.H. et al. [29] suggested the use of YOLOv4 to employ computer vision approaches to identify carious Lesions from microphotography images taken by different Smartphone. Improved datasets brought significant changes improving model training; the sensitivity attained at 0.99 while specificity attained at 0.94. Even though the research resulted with the better robustness for the images derived from smartphones, the method needs augmentation when facing the dataset variability, making it impractical for non-expert in the clinics.

2.2 Segmentation Models

Rashid, U. et al. [27] presented the fusion model of the Mask RCNN that was designed to identify the position of dental cavities in colored photo images and X-ray images. The approach implemented the flexibility in diagnosis utilizing a mixed data set of annotated images. The system accuracy was ranging from 78–92% whereas overall dentist satisfaction percentage was above 80%. Nevertheless, the model is highly generalized, and its application is associated with the necessity for thorough annotation, as well as high computational demands, which poses challenges for its use in environments of limited resources.

2.3 Classification Models

Ragodos, R. et al. [24] trained the DNN to recognize 10 dental abnormalities, hypoplasia, microdontia on the large intraoral images dataset and impacted teeth particularly in children with OFC. This classifying technique which is multi-class classification got F1 score that was nearly similar to the score that experienced dentists got in detecting seven of the anomalies. The study emphasised that the model is particularly rapid and accurate in detecting anomalies, but low effective for particular anomalies and requires extensive data annotation.

Ahmed, W.M. et al. [28] employed CNN to identify the different caries types from dental images of multiple datasets. Bitewings radiographs with a resolution of 1876×1402 pixels were gathered, segmented, and anonymised using a dental caries analysis software application. The strategy used supervised learning algorithms trained for semantic segmentation tasks. This approach achieved a superior classification results, establishing itself as a sensitive and precise approach that excels in all evaluated classes. However, the model requires huge computation which makes it very hard to apply in real-time and widely if not supported by adequate hardware.

2.4 Transfer Learning Models

Qayyum, A. et al. [30] presented a semi-supervised learning framework to address the issues of limited size and quality of the annotated dataset for caries detection in dental radiographs. Using the teacher-student network methodology that incorporated both labeled and unlabeled images, the method obtained 6 percent absolute enhancement in pixel accuracy and 3% on mIoU. The framework does not rely heavily on annotated data but does require high quality radiographs and computational resources for training.

3 Comparative Analysis

In this section, various DL approaches are compared in terms of the methods used, the advantages observed, the limitations and the performance measures as detailed in table 1.

Table 1: Comparative analysis of various DL approaches.

Author	Methodology	Advantage	Limitation	Performance Measure
Thanh, M.T.G. et al. [21]	Applied YOLOv3 and Faster R-CNN to detect dental caries using smartphone images	Accessible via smartphones; high sensitivity for cavitated caries	Low sensitivity for non-cavitated caries; dependent on image quality	Sensitivity and Specificity
Xiong, Y. et al. [22]	Developed ToothNet based on YOLOX framework for simultaneous detection of caries and fissure sealants	Simultaneously detects caries and fissure sealants with high accuracy	Performance limited to confidence thresholds; requires annotated datasets	AUC, Sensitivity, Precision
Ding, B et al. [23]	Used YOLOv3 with augmented and enhanced datasets for caries detection in oral photographs	Combines multiple datasets to improve model generalizability	Lower recall for secondary caries; challenges with non-standardized photos	mAP, Precision, Recall
Ragodos, R. et al. [24]	Trained a DNN on intraoral images for multi-class classification of dental anomalies in children with OFC	Handles multi-class anomalies, improving anomaly detection speed	Struggles with three specific anomalies; dependent on extensive annotations	F1 scores
Tareq, A et al. [25]	Proposed a hybrid YOLO ensemble with transfer learning for non-standardized smartphone photos	Adapts to non-standardized images for remote diagnostics	Requires high-quality non-standardized images for optimal results	Diagnostic accuracy, Precision, Recall
Bayraktar, Y et al. [26]	Modified YOLO for detecting interproximal caries in bitewing radiographs	High specificity and sensitivity for detecting interproximal caries	Limited by dataset size; moderate sensitivity for molar caries	Accuracy, Sensitivity, Specificity

Rashid, U. et al. [27]	Developed a hybrid Mask RCNN model for detecting cavities in mixed photographic and X-ray images	Combines various image types for comprehensive analysis	Dependent on expert annotations; hardware-intensive model	Accuracy
Ahmed, W.M. et al. [28]	Applied AI for detection and classification of caries using CNNs on various dental datasets	Provides robust classification across various dental caries types	Requires extensive computational resources; not suitable for real-time analysis	Robust classification performance
Farook, T.H. et al. [29]	Used YOLO.v4 for caries classification from microphotography across smartphones	Demonstrates adaptability across devices with high accuracy	Relies on augmentation to overcome limited dataset sizes	Sensitivity, Specificity
Qayyum, A. et al. [30]	Proposed a self-supervised learning framework using a teacher-student model for dental radiographs	Efficiently trains with limited annotated data	Dependent on high-quality radiographs; computationally intensive	Pixel accuracy improvement, mIoU improvement

4 Challenges

- One of the main challenges that observed is the availability of a large-scale dataset annotated to support deep learning for dental caries detection. To train effective models, which are difficult to overfit, a diverse and well-labelled data is required, but annotating such data is costly and time-consuming. Additionally, the datasets also face problems such as imbalance where some types of caries are less present during diagnosis, for instance, secondary caries or caries at the early stage. This skews the model's responses, and decreases their accuracy when predicting less common caries types.
- The variability in the imaging techniques is a serious challenge. The images may be produced from capture with smartphones or conventional intraoral images. Images which are not standardized, like taking photos using smartphone, with different environment leads to slight variation as to the model. Moreover, pre-training multiple modalities including photographic and radiographic images also, amplifies the difficulty and computational cost of the models.
- Overfitting is also a major problem in DL models, and even more so in a few or augmented learning sets. Although techniques like Augmentation provide ways by which datasets can be artificially enlarged some of these datasets may not represent the variability of the real world. Therefore, models developed with a limited sample will be accurate in the initial dataset but less so on new clinical data. This lack of

generalizability can be especially severe when using models within different populations of patients, individuals with different overall oral health status.

- While most models offer satisfactory diagnostic accuracy for cavitated caries with well-defined characteristics, they do not provide definitions of initial or proximal caries. The limitation in this area can be observed in the early stages of diagnostics and treatment when a disease is still in its stages when it has not had the time to progress. Systems that are dependent on easily distinguishable interfaces fail to pick such borderline cases, which limits their usefulness in a clinic.
- The current DL models, especially those models that implement more sophisticated architecture such as YOLO, or the Mask RCNN, need significantly high computational resources at both, the training and inference phases. This makes them unsuitable for deployment in resource limited areas or on low cost devices such as smart phones. However, the problem of real time computations has not been solved with powerful though mobile devices indeed have become.

5 Summary

The overall survey discusses the researches on the identification of the dental caries using DL models such as YOLO, Mask RCNN, and CNNs for processes that feature lesion segmentation, classification, and detection on intraoral and radiographic views. While these methods showed high accuracy and sensitivity, problems related to high quality annotated datasets, non-standardized imaging and the low rate of early stage or secondary caries were reported. To address these research gaps, the current study suggests the use complex methods such as the hybrid and semi-supervised models while avoiding over-reliance on the dataset. in this way, multiple sources of imaging, such as smartphone camera images and conventional radiographs, with improved data enhancement for effective model training can be integrated. By providing a comprehensive taxonomy and performance comparison, this research highlights the strengths and limitations of existing methods, offering a framework for future developments. These efforts pave the way for scalable, accurate, and efficient diagnostic tools that can be effectively deployed in diverse clinical settings.

6 Conclusion

The overall survey discusses the researches on the identification of the dental caries using DL models such as YOLO, Mask RCNN, and CNNs for processes that feature lesion segmentation, classification, and detection on intraoral and radiographic views. While these methods showed high accuracy and sensitivity, problems related to high quality annotated datasets, non-studarized imaging and the low rate of early stage or secondary caries were reported. To address these research gaps, the current study suggests the use complex methods such as the hybrid and semi-supervised models while avoiding over-reliance on the dataset. in this way, multiple sources of imaging, such as smartphone camera images and conventional radiographs, with improved data enhancement for effective model training can be integrated. By providing a comprehensive taxonomy and performance comparison, this research highlights the strengths and limitations of existing methods, offering a framework for future developments. These efforts pave the way for scalable, accurate, and efficient diagnostic tools that can be effectively deployed in diverse clinical settings.

References

[1] Musri, N., Christie, B., Ichwan, S.J.A. and Cahyanto, A., 2021. Deep learning convolutional neural network algorithms for the early detection and diagnosis of dental caries on periapical radiographs: A systematic review. *Imaging science in dentistry*, *51*(3), p.237.

[2] Chen, X., Guo, J., Ye, J., Zhang, M. and Liang, Y., 2022. Detection of proximal caries lesions on bitewing radiographs using deep learning method. *Caries Research*, *56*(5-6), pp.455-463.

[3] Imak, A., Celebi, A., Siddique, K., Turkoglu, M., Sengur, A. and Salam, I., 2022. Dental caries detection using score-based multi-input deep convolutional neural network. *IEEE Access*, *10*, pp.18320-18329.

[4] Holtkamp, A., Elhennawy, K., Cejudo Grano de Oro, J.E., Krois, J., Paris, S. and Schwendicke, F., 2021. Generalizability of deep learning models for caries detection in near-infrared light transillumination images. *Journal of clinical medicine*, *10*(5), p.961.

[5] Talpur, S., Azim, F., Rashid, M., Syed, S.A., Talpur, B.A. and Khan, S.J., 2022. Uses of different machine learning algorithms for diagnosis of dental caries. *Journal of Healthcare Engineering*, *2022*(1), p.5032435.

[6] Duong, D.L., Kabir, M.H. and Kuo, R.F., 2021. Automated caries detection with smartphone color photography using machine learning. *Health informatics journal*, *27*(2), p.14604582211007530.

[7] Vinayahalingam, S., Kempers, S., Limon, L., Deibel, D., Maal, T., Hanisch, M., Bergé, S. and Xi, T., 2021. Classification of caries in third molars on panoramic radiographs using deep learning. *Scientific reports*, *11*(1), p.12609.

[8] Majanga, V. and Viriri, S., 2022. A survey of dental caries segmentation and detection techniques. *The Scientific World Journal*, *2022*(1), p.8415705.

[9] Bui, T.H., Hamamoto, K. and Paing, M.P., 2022. Automated caries screening using ensemble deep learning on panoramic radiographs. *Entropy*, *24*(10), p.1358.

[10] Chawla, R., Krishna, K.H., Deshmukh, A.A., Sagar, K.D., Al Ansari, M.S. and Taloba, A.I., 2022. A hybrid optimization approach with deep learning technique for the classification of dental caries. *International Journal of Advanced Computer Science and Applications*, *13*(12).

[11] Zhang, X., Liang, Y., Li, W., Liu, C., Gu, D., Sun, W. and Miao, L., 2022. Development and evaluation of deep learning for screening dental caries from oral photographs. *Oral diseases*, *28*(1), pp.173-181.

[12] Park, E.Y., Cho, H., Kang, S., Jeong, S. and Kim, E.K., 2022. Caries detection with tooth surface segmentation on intraoral photographic images using deep learning. *BMC Oral Health*, *22*(1), p.573.

[13] Kühnisch, J., Meyer, O., Hesenius, M., Hickel, R. and Gruhn, V., 2022. Caries detection on intraoral images using artificial intelligence. *Journal of dental research*, *101*(2), pp.158-165.

[14] Lian, L., Zhu, T., Zhu, F. and Zhu, H., 2021. Deep learning for caries detection and classification. *Diagnostics*, *11*(9), p.1672.

[15] Liu, Y., Cheng, Y., Song, Y., Cai, D. and Zhang, N., 2024. Oral screening of dental calculus, gingivitis and dental caries through segmentation on intraoral photographic images using deep learning. *BMC Oral Health*, *24*(1), p.1287.

[16] van Nistelrooij, N., Chaves, E.T., Cenci, M.S., Cao, L., Loomans, B.A., Xi, T., El Ghoul, K., Romero, V.H.D., Lima, G.S., Flügge, T. and van Ginneken, B., 2024. Deep learning-based algorithm for staging secondary caries in bitewings. *Caries Research*, pp.1-21.

[17] Makarim, A.F., Karlita, T., Sigit, R., Dewantara, B.S.B. and Brahmanta, A., 2024. Deep Learning Models for Dental Conditions Classification Using Intraoral Images. *JOIV: International Journal on Informatics Visualization*, *8*(3), pp.1099-1108.

[18] Zhang, R., Lu, M., Zhang, J., Chen, X., Zhu, F., Tian, X., Chen, Y. and Cao, Y., 2024. Research and Application of Deep Learning Models with Multi-Scale Feature Fusion for Lesion Segmentation in Oral Mucosal Diseases. *Bioengineering*, *11*(11), p.1107.

[19] . Park, E.Y., Jeong, S., Kang, S., Cho, J., Cho, J.Y. and Kim, E.K., 2023. Tooth caries classification with quantitative light-induced fluorescence (QLF) images using convolutional neural network for permanent teeth in vivo. *BMC Oral Health*, *23*(1), p.981.

[20] Tan, R., Zhu, X., Chen, S., Zhang, J., Liu, Z., Li, Z., Fan, H., Wang, X. and Yang, L., 2024. Caries lesions diagnosis with deep convolutional neural network in intraoral QLF images by handheld device. *BMC Oral Health*, *24*(1), p.754.

[21] Thanh, M.T.G., Van Toan, N., Ngoc, V.T.N., Tra, N.T., Giap, C.N. and Nguyen, D.M., 2022. Deep learning application in dental caries detection using intraoral photos taken by smartphones. *Applied Sciences*, *12*(11), p.5504.

[22] Xiong, Y., Zhang, H., Zhou, S., Lu, M., Huang, J., Huang, Q., Huang, B. and Ding, J., 2024. Simultaneous detection of dental caries and fissure sealant in intraoral photos by deep learning: a pilot study. *BMC Oral Health*, *24*(1), p.553.

[23] Ding, B., Zhang, Z., Liang, Y., Wang, W., Hao, S., Meng, Z., Guan, L., Hu, Y., Guo, B., Zhao, R. and Lv, Y., 2021. Detection of dental caries in oral photographs taken by mobile phones based on the YOLOv3 algorithm. *Annals of Translational Medicine*, *9*(21).

[24] Ragodos, R., Wang, T., Padilla, C., Hecht, J.T., Poletta, F.A., Orioli, I.M., Buxó, C.J., Butali, A., Valencia-Ramirez, C., Restrepo Muñeton, C. and Wehby, G.L., 2022. Dental anomaly detection using intraoral photos via deep learning. *Scientific reports*, *12*(1), p.11577.

[25] Tareq, A., Faisal, M.I., Islam, M.S., Rafa, N.S., Chowdhury, T., Ahmed, S., Farook, T.H., Mohammed, N. and Dudley, J., 2023. Visual diagnostics of dental caries through deep learning of non-standardised photographs using a hybrid YOLO ensemble and transfer learning model. *International Journal of Environmental Research and Public Health*, *20*(7), p.5351.

[26] Bayraktar, Y. and Ayan, E., 2022. Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. *Clinical oral investigations*, *26*(1), pp.623-632.

[27] Rashid, U., Javid, A., Khan, A.R., Liu, L., Ahmed, A., Khalid, O., Saleem, K., Meraj, S., Iqbal, U. and Nawaz, R., 2022. A hybrid mask RCNN-based tool to localize dental cavities from real-time mixed photographic images. *PeerJ Computer Science*, *8*, p.e888.

[28] Ahmed, W.M., Azhari, A.A., Fawaz, K.A., Ahmed, H.M., Alsadah, Z.M., Majumdar, A. and Carvalho, R.M., 2023. Artificial intelligence in the detection and classification of dental caries. *The Journal of Prosthetic Dentistry*.

[29] Farook, T.H., Ahmed, S., Jamayet, N.B. and Dudley, J., 2023. Computer vision with smartphone microphotography for detection of carious lesions. *Intelligence-Based Medicine*, *8*, p.100105.

[30] Qayyum, A., Tahir, A., Butt, M.A., Luke, A., Abbas, H.T., Qadir, J., Arshad, K., Assaleh, K., Imran, M.A. and Abbasi, Q.H., 2023. Dental caries detection using a semi-supervised learning approach. *Scientific Reports*, *13*(1), p.749.