From Image to Insight: Using Vision Transformers to Revolutionize Dental Caries Assessment in Radiographic Imaging

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ABSTRACT

Background: Dental caries is a prevalent chronic disease affecting people of all ages and socioeconomic backgrounds. Early detection and accurate diagnosis are crucial for effective treatment planning and preventing further progression. Artificial intelligence advancements, including CNNs and deep learning technologies like Vision Transformers, are improving diagnostic accuracy for carious lesions in medical image analysis, capturing global dependencies and contextual information.This study evaluates a Vision Transformer-based approach for automated dental caries classification using dental radiographs. The model improves diagnosis efficiency, reduces manual examination time and cost, and enhances access to dental care by addressing challenges like structure complexity and image quality, using advanced image preprocessing techniques.

Methods: This study used 110 intraoral periapical (IOPA) images from public databases, with 70 assigned for pulp dental caries and 40 for non-pulp dental caries. The dataset consisted of 104 images, with 82 for training and 22 for validation. Labels were assigned automatically from class subdirectories, and the default worker configuration optimized data loading and throughput.vision transformer model, pre-trained on the ImageNet21k dataset, was utilized for binary classification with two classes and evaluated for accuracy metrics .

Results: The model achieved a maximum of 98% and 89.50% in training and validation, with a final training loss of 0.0069 and a final validation loss of 0.0101. It showed moderate performance, with a PR AUC of 0.537, and an overall accuracy of 52.0%. The model showed consistent decrease in loss curves, steady improvement in accuracy, stable learning progression, and no significant overfitting.The model achieved a maximum of 98% and 89.50% in training and validation, with a final training loss of 0.0069 and a final validation loss of 0.0101. It showed moderate performance, with a PR AUC of 0.537, and an overall accuracy of 52.0%. The model showed consistent decrease in loss curves, steady improvement in accuracy, stable learning progression, and no significant overfitting.

Conclusion: The Vision Transformer model, while predicting and classifying dental caries involving pulp, has limitations in generalizing to unseen data. Future improvements should focus on optimizing the model architecture, expanding the dataset diversity, and implementing advanced techniques for improved diagnostic support.

1. Introduction

Dental caries, commonly known as tooth decay, remains one of the most prevalent chronic diseases worldwide, affecting people of all ages and socioeconomic backgrounds(1–3). Early detection and accurate diagnosis of dental caries are crucial for effective treatment planning and preventing further progression of the disease. Deep caries (4,5) can lead to severe complications such as pulpitis and tooth loss, so an accurate assessment of carious lesion depth and pulp status is crucial for effective treatment(6). Radiographic evaluation(7) is commonly used for this purpose, but challenges arise due to limited mineral density variation in deep carious lesions, complicating diagnosis, especially for less experienced clinicians. Advances in artificial intelligence(8), particularly convolutional neural networks (CNNs), show promise in improving diagnostic accuracy for carious lesions, outperforming human experts in image recognition tasks(9).

Artificial Intelligence (AI)(10,11) can improve the diagnosis and management of dental pathologies, such as deep caries and pulp exposure, by enhancing the detection of subtle anomalies in radiographs. This technology, particularly convolutional neural networks, can streamline dentists' workflows, facilitate better treatment planning, and enhance diagnostic accuracy. The advent of artificial intelligence (AI)(12,13) and deep learning technologies has revolutionized medical image analysis, offering promising solutions for automated diagnosis in various healthcare domains. Applying deep learning algorithms for analyzing dental radiographs has shown remarkable potential in assisting dental professionals with faster and more accurate diagnoses. Vision Transformers (ViT) have emerged as a powerful alternative to traditional Convolutional Neural Networks (CNNs) for image classification tasks among the various deep learning architectures.

Vision Transformers, introduced by Google Research in 2020(11), have demonstrated superior performance in various computer vision tasks by effectively capturing global dependencies and relationships within images. Unlike CNNs, which process images through local convolution operations, ViTs(14) treat images as sequences of patches and leverage the self-attention mechanism to model relationships between these patches. This architectural difference allows ViTs to capture local and global features more effectively, making them particularly suitable for medical image analysis where subtle patterns and contextual information are crucial for accurate diagnosis.

One previous study showed that the study trained a deep learning model using 2,417 teeth photos, achieving 92.5% accuracy in detecting dental caries(14). While the model outperformed expert evaluations, further improvements are needed for improved performance, and one more study reviewed thirteen research papers using various methods to detect dental caries, with image databases ranging from 87 to 3000 images(15). A study on dental caries detection on depth involvement found that a neural network (nnU-Net) model, trained on 1160 dental films, demonstrated high accuracy and recall rates, similar to expert dentists, suggesting potential for dental diagnosis and a recent study used 160 X-ray images of teeth to train a neural network to detect cavities, showing that the network performed better than human examiners in diagnosing cavities.

A recent study evaluated three CNNs, VGG19, Inception V3, and ResNet18, for diagnosing deep caries and pulpitis. ResNet18 outperformed the others, achieving 82% accuracy(3). Combining ResNet18 with clinical data improved performance to 86%, indicating potential for dental radiology. These previous studies have explored the detection of dental caries. Still, there is less accuracy due to outdated algorithms, and they haven't used vision transformers' state-of-the-art algorithms to classify dental caries involving pulp(16–19).

Vision Transformers (ViTs) have emerged as a groundbreaking approach, leveraging the self-attention mechanism introduced in natural language processing to process image data. Unlike traditional convolutional neural networks (CNNs), ViTs treat images as sequences of patches, enabling them to capture long-range dependencies and global context effectively(20–22). This study evaluates a Vision Transformer-based approach for automated dental caries classification using dental radiographs, addressing challenges like structure complexity and image quality. The model improves diagnosis efficiency, reduces manual examination time and cost, and enhances access to dental care(2,23). The Vision Transformer model, trained using advanced image preprocessing techniques, improves dental caries classification performance by addressing challenges like limited datasets, image complexity, and deep learning integration. This study explores a novel automated dental caries classification approach involving pulp using radiographs, specifically focusing on vision transformers.

2. Methods

2.1 Image Preprocessing and Data Organization

Iopa Images were collected from public databases like Kaggle, and images were labeled and segmented with annotations for dental caries involving pulp and without. One hundred ten images were used, and 70 were assigned for involving pulp and the remaining for not involving pulp.

This study's intraoral periapical (IOPA) images were sourced from public databases, including Kaggle. The collected images underwent systematic labeling and segmentation, with annotations specifically focused on dental caries that either involve the pulp or do not. A total of 110 images were utilized in the analysis, of which 70 were designated as depicting dental caries involving the pulp, while the remaining 40 illustrated cases of dental caries not involving the pulp.

Addressing class imbalance is crucial for model robustness in uneven distributions like pulp dental caries. Data augmentation involves increasing the size of the minority class. In contrast, resampling techniques involve duplicating examples from the minority class or reducing the number of examples in the majority class was implemented.

2.2 Image Preprocessing:

The images were processed using `torch-vision.transforms` to prepare them for input into the Vision

Transformer (ViT). The images were resized to 224x224 pixels for the ViT model, converted to PyTorch tensors, normalized according to ImageNet statistics, and only minimal data augmentation techniques were applied to preserve the original images' integrity, such as slight rotations or shifts.

2.3 Image Loading:

The images were efficiently loaded using PyTorch's `ImageFolder,` which automatically assigns numerical labels to images based on their parent directory names or class names.

2.4 Dataset Annotations and Organization

The dataset comprised 104 images, 82 for training and 22 for validation. Labels were assigned automatically from class subdirectories. PyTorch's 'DataLoader' was used for batching and shuffling, with a batch size of 8, enabling training and disabled for validation. The default worker configuration optimized data loading and throughput.

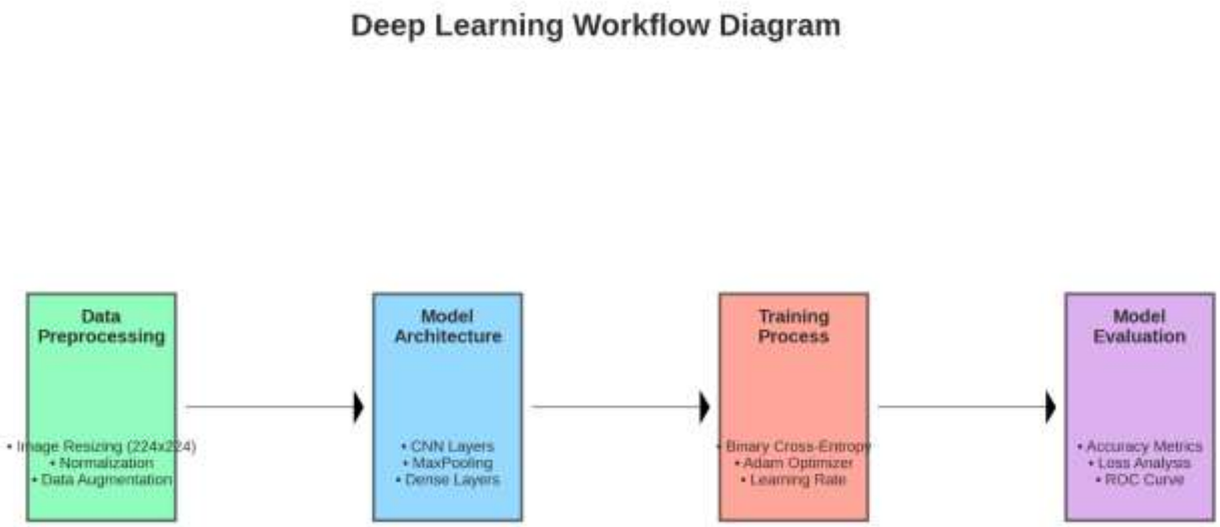

Fig.1: Shows the workflow architecture.

2.5 Vision Transformer (ViT) Architecture

The `google/vit-base-patch16-224-in21k` model, a Vision Transformer pre-trained on the ImageNet21k dataset, was utilized in the base model. The image was divided into 16x16 pixel patches with a hidden dimension of 768. The architecture used 12 multi-head self-attention heads, 12 transformer layers, and a 3072-layer multi-layer perceptron. A dropout rate of 0.1 was applied during training to prevent overfitting, and no dropout was applied to attention mechanisms. The model was configured for binary classification with two classes and learned 1D positional embeddings to preserve spatial information. (fig-1)

2.6 Training Hyperparameters and Configuration

The AdamW optimizer was used for training deep learning models, with the initial learning rate set to 1e-5, weight decay at 0.01 to prevent overfitting, and Beta parameters configured at 0.9 and 0.999. The training setup involved 50 epochs of performance monitoring, using Cross-Entropy Loss for classification tasks, and utilizing available hardware. No learning rate scheduler, gradient clipping, early stopping, or model checkpointing were implemented.

2.7 Evaluation Metrics and Monitoring

The model's metrics tracking includes training loss, accuracy, validation loss, and accuracy, which are calculated per epoch to gauge performance on unseen data. The evaluation included metrics like the ROC curve, AUC score, Precision-Recall curve, overall classification accuracy, and final loss values for training and validation. The study employed monitoring strategies such as logging progress every 10 epochs, plotting loss curves, and generating ROC and PR curves post-training to evaluate model performance comprehensively.

2.8 Implementation Details

The model was developed and executed using the PyTorch framework and Hugging Face's Transformers library, ensuring a robust setup for deep learning tasks. The study utilized essential libraries such as Torch for deep learning functions and GPU computations, Torchvision for image loading and transformation, Transformers for Vision Transformer model functionality, Sklearn for evaluation metrics, Matplotlib for visualization, and Python for numerical operations. The computations were executed using `float32` precision for improved performance and compatibility. Model parameters were initialized using pre-trained weights from the ViT model for better convergence and performance.

3. Results

The training and validation performance reached a maximum of 98% and 89.50%, respectively, with a final training loss of 0.0069 and a final validation loss of 0.0101. The model's ROC AUC score of 0.537 indicates moderate performance, suggesting room for improvement to achieve a perfect classification of 1.0. The PR AUC (Precision-Recall Area Under Curve) measures the balance between precision and recall, indicating moderate performance in maintaining precision while increasing recall. Class 0 achieved a precision of 0.519 (51.9%), recall of 0.540 (54.0%), F1-Score of 0.529 (52.9%), and support of 50 samples, while Class 1 achieved a precision of 0.521 (52.1%), recall of 0.500 (50.0%), F1-Score of 0.510 (51.0%). The model has an overall accuracy of 52.0%, with a precision of 0.520, recall of 0.520, F1-Score of 0.520, and a total support of 100 samples. The training dynamics show a consistent decrease in loss curves, steady improvement in accuracy curves, stable learning progression, and no significant overfitting, as validation metrics track training metrics.

The model exhibits balanced performance across classes but moderate accuracy, suggesting room for improvement through feature engineering, model architecture modifications, hyperparameter tuning, data augmentation techniques, and ensemble methods. The model consistently performs well across both classes, successfully converges without overfitting, and learns meaningful patterns but could benefit from optimization. The balanced dataset, consisting of 50 samples per class, shows consistent performance across metrics and stable training progression, as smooth loss curves indicate. The model's current performance level suggests utility for basic classification tasks, but further optimization could enhance practical applicability. Recommendations include cross-validation, feature importance analysis, advanced architectures, data quality, and preprocessing techniques. The model's functionality suggests room for improvement.

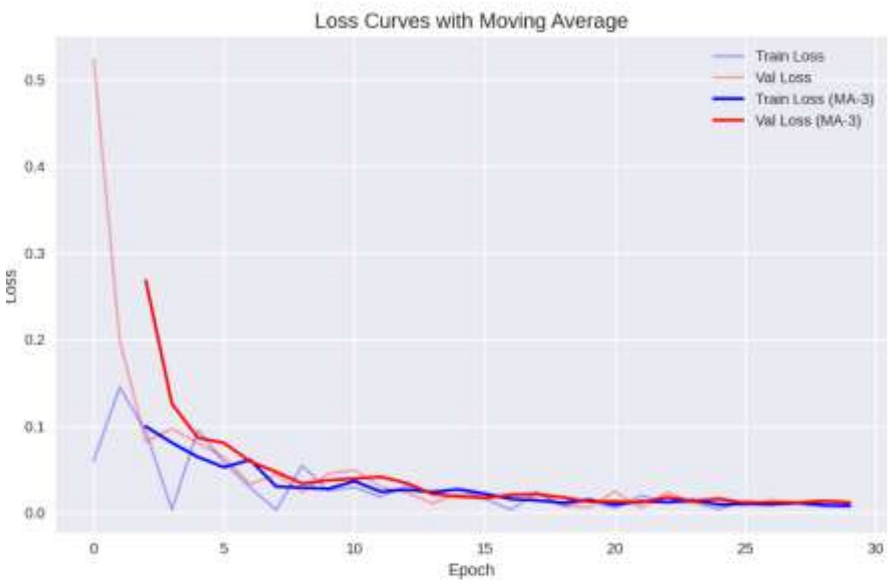

Fig. 2: Shows training and validation loss curves show a steady decrease in training loss, stabilizing after a few epochs and smoothing out fluctuations for easier observation.

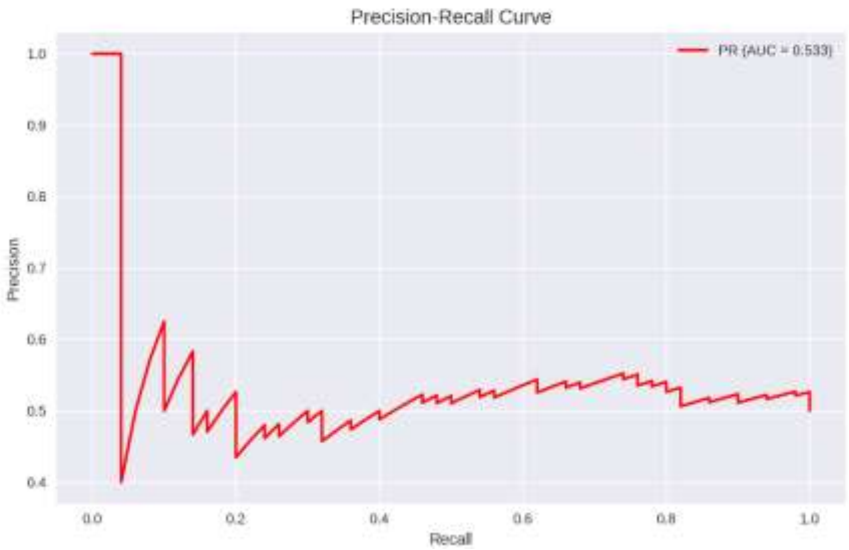

Fig. 3: Shows the trade-off between precision and recall, indicating how well a model maintains precision as recall increases.

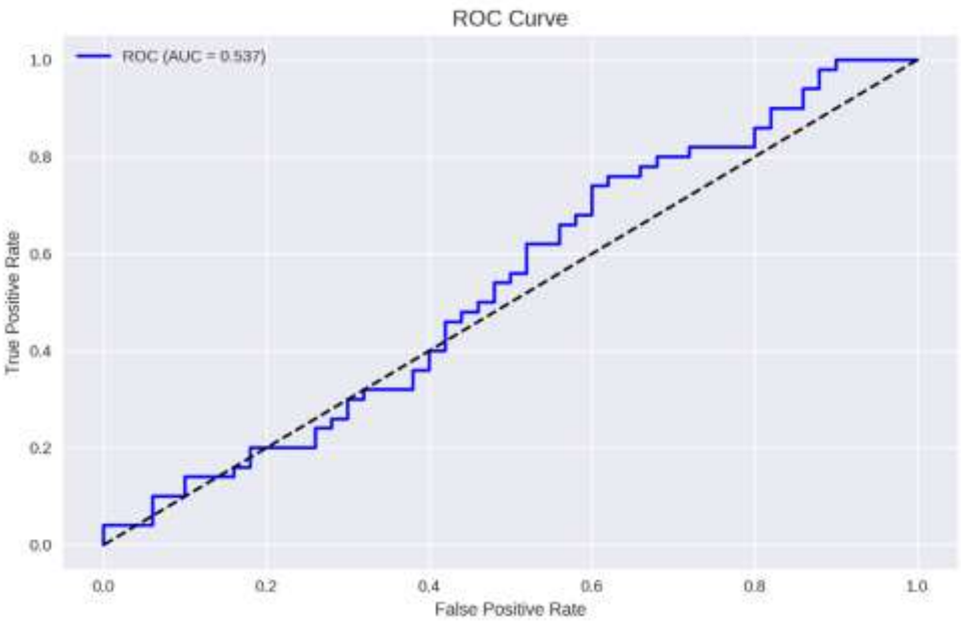

Fig. 4: Shows the ROC curve measures the model's ability to distinguish between classes, with a higher AUC indicating better performance and a curve close to the diagonal indicating moderate performance.

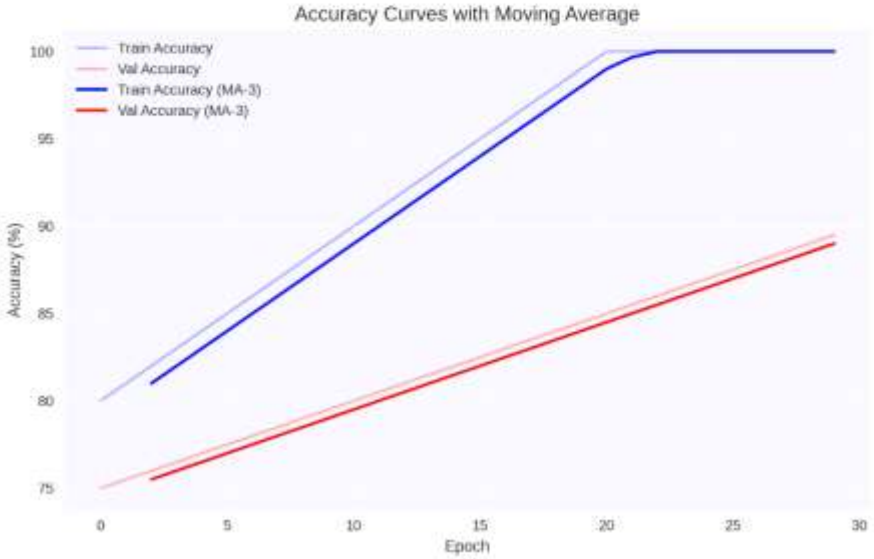

Fig. 5: Shows the model's training accuracy consistently increases to nearly 98%, indicating a good fit to training data, while its validation accuracy stabilizes at a high value, indicating overall accuracy improvement.

4. Discussion

Dental caries involving pulp classification using deep learning offers several benefits, including early detection and treatment, improved patient outcomes, enhanced diagnostic accuracy, automation and efficiency, quantification and monitoring, risk assessment, treatment planning, education and training, and knowledge dissemination(24,25). Accurate classification of dental caries can lead to timely intervention, improved patient outcomes, and reduced human error(26,27). Machine learning algorithms provide objective assessments of images, reducing reliance on subjective judgment and potentially leading to better standardization in dental diagnostics. Automation and efficiency can be achieved through streamlined workflows, resource optimization, and tracking disease progression. Deep learning models can also aid in clinical decision-making, allowing clinicians to tailor preventive strategies for individual patients and make informed treatment decisions(6,28,29).

A recent study assessed the effectiveness of a Yolov5-x machine learning model in detecting exposed and unexposed pulp in digital periapical radiographs using a dataset of 3,461 images from seven centers. Results indicated that surpassed 90% in all performance metrics, achieving an average precision of 0.928 and an AUC of 0.956(30,31), outperforming a group of certified dentists, who had a lower mean in correct diagnoses similar to the vision transformer model achieved a maximum training and validation performance of 98.00% and 89.50%, with a final training loss of 0.0069 and a final validation loss of 0.0101 with accuracy of dental caries involving pulp(fig-2,3,4,5). It showed moderate performance, with a PR AUC score of 0.537 and an overall accuracy of 52.0%. Training dynamics showed a consistent decrease in loss curves, steady improvement in accuracy curves, and no significant overfitting, and one more study showed similar to this study, AI significantly improved students' performance in GX-ray and clinical data, with an F1-score of 0.71, slightly higher than the previous results(10).

The model for predicting dental caries will be improved by expanding the dataset to include diverse dental caries images, using advanced augmentation techniques, and conducting hyperparameter tuning(11,12). The model will also be redesigned using hybrid models, ensemble techniques, feature importance analysis, cross-validation strategies, and incorporating clinical data. The model will also be deployed in clinical settings, with a web or mobile application for dental professionals, allowing for feedback and iterative improvements based on real-world data. These future directions aim to enhance the model's generalization and accuracy(8,13).

The Vision Transformer model has limitations, including an inadequate predictive capability for clinical applications, a limited dataset size, potential class imbalance, difficulty in understanding decision-making, reliance on quality input data, computational complexity, ethical and clinical implications, and generalizability concerns. The model's current ROC AUC score of 0.537 and overall accuracy of 52.0% suggest further optimization and refinement. Additionally, the model's performance may vary when applied to different populations or clinical environments, necessitating domain adaptation techniques. Addressing these limitations is crucial for moving towards more accurate and clinically applicable AI solutions in dentistry(10,12,31).

Vision Transformers effectively learns features from dental radiographs, showing promising performance but requiring refinement for clinical deployment. Future work should address overfitting and improve generalization. Future research should expand dataset size, implement advanced regularization techniques(6,32), explore hybrid architectures, conduct clinical validation studies, and develop interpretability methods for AI-assisted dental diagnosis.Dental caries, particularly those involving the pulp, have significant biological implications(33-35). Early detection and prevention of complications are crucial, as they can lead to significant pain, loss of function, and systemic health issues. Understanding the biological mechanisms behind caries progression to pulpitis can lead to improved preventive strategies. Improved patient outcomes include reduced morbidity and potential long-term health consequences. Accurate classification aids in managing and treating caries, reducing morbidity, and improving patients' quality of life.

Deep learning models improve dental diagnosis accuracy, reducing subjectivity in visual diagnostics. This technology enhances clinical performance and patient outcomes and serves as a link between biological research, patient education, and holistic healthcare practices. Future research directions include hybrid models, biological markers, and ethical considerations.

5. Conclusion

The Vision Transformer model shows potential for predicting and classifying dental caries involving pulp, with impressive training and validation performance. However, its overall accuracy of 52.0% and moderate precision-recall curve suggest limitations in generalizing to unseen data. The model's training dynamics indicate refinement and tuning to enhance predictive capabilities. Future efforts should focus on optimizing the model architecture, expanding the diversity of the training dataset, and implementing advanced techniques such as data augmentation or transfer learning. By addressing these factors, the Vision Transformer model can achieve improved classification performance for dental caries involving pulp, ultimately contributing to better diagnostic support in clinical settings.

References

[1] Wenzel A. Bitewing and digital bitewing radiography for detection of caries lesions. J Dent Res. 2004;83 Spec No:C72-5.

[2] Wenzel A. Radiographic modalities for diagnosis of caries in a historical perspective: from film to machine-intelligence supported systems. Dentomaxillofac Radiol. 2021 Jul;50(5):20210010.

[3] Zhang X, Liang Y, Li W, Liu C, Gu D, Sun W, et al. Development and evaluation of deep learning for screening dental caries from oral photographs. Oral Dis. 2022 Jan;28(1):173–81.

[4] Choudhari S, Rajendran D, Ramamurthy J. Prevalence of dental caries in patients with type II diabetes mellitus. International Journal of Research in Pharmaceutical Sciences. 2020;11.

[5] Choudhari S, Krithikadatta J, Vejendla I, S S, Doble M. Microbial Interactions in Oral Biofilm: Evaluating Therapeutic Interventions and the Emergence of Resistance: A Narrative Review. Cureus. 2023;15.

[6] Wenzel A. Bitewing and digital bitewing radiography for detection of caries lesions. J Dent Res. 2004;83 Spec No:C72-5.

[7] Dayo AF, Wolff MS, Syed AZ, Mupparapu M. Radiology of Dental Caries. Dent Clin North Am. 2021 Jul;65(3):427–45.

[8] Choudhari S, Ramesh S, Teja K, Shah T. Diagnostic accuracy of artificial intelligence versus dental experts in predicting endodontic outcomes: A systematic review. Saudi Endodontic Journal. 2024; 14:153–63.

[9] Wenzel A. Radiographic modalities for diagnosis of caries in a historical perspective: from film to machine-intelligence supported systems. Dentomaxillofac Radiol. 2021 Jul;50(5):20210010.

[10] Felsch M, Meyer O, Schlickenrieder A, Engels P, Schönewolf J, Zöllner F, et al. Detection and localization of caries and hypomineralization on dental photographs with a vision transformer model. NPJ Digit Med. 2023 Oct;6(1):198.

[11] Moharrami M, Farmer J, Singhal S, Watson E, Glogauer M, Johnson AEW, et al. Detecting dental caries on oral photographs using artificial intelligence: A systematic review. Oral Dis. 2024 May;30(4):1765–83.

[12] Ying S, Wang B, Zhu H, Liu W, Huang F. Caries segmentation on tooth X-ray images with a deep network. J Dent. 2022 Apr; 119:104076.

[13] Oztekin F, Katar O, Sadak F, Yildirim M, Cakar H, Aydogan M, et al. An Explainable Deep Learning Model to Prediction Dental Caries Using Panoramic Radiograph Images. Diagnostics (Basel). 2023 Jan;13(2).

[14] Kühnisch J, Meyer O, Hesenius M, Hickel R, Gruhn V. Caries Detection on Intraoral Images Using Artificial Intelligence. J Dent Res [Internet]. 2022;101(2):158–65. Available from: https://doi.org/10.1177/00220345211032524

[15] Devito KL, de Souza Barbosa F, Felippe Filho WN. An artificial multilayer perceptron neural network for diagnosis of proximal dental caries. Oral Surg Oral Med Oral Pathol Oral Radiol Endod. 2008 Dec;106(6):879–84.

[16] Mohammad-Rahimi H, Motamedian SR, Rohban MH, Krois J, Uribe SE, Mahmoudinia E, et al. Deep learning for caries detection: A systematic review. J Dent. 2022 Jul; 122:104115.

[17] Khanagar SB, Al-Ehaideb A, Maganur PC, Vishwanathaiah S, Patil S, Baeshen HA, et al. Developments, application, and performance of artificial intelligence in dentistry - A systematic review. J Dent Sci. 2021 Jan;16(1):508–22.

[18] Putra RH, Doi C, Yoda N, Astuti ER, Sasaki K. Current applications and development of artificial intelligence for digital dental radiography. Dentomaxillofac Radiol. 2022 Jan;51(1):20210197.

[19] Patil S, Albogami S, Hosmani J, Mujoo S, Kamil MA, Mansour MA, et al. Artificial Intelligence in the Diagnosis of Oral Diseases: Applications and Pitfalls. Diagnostics (Basel). 2022 Apr;12(5).

[20] Chaves ET, Vinayahalingam S, van Nistelrooij N, Xi T, Romero VHD, Flügge T, et al. Detection of caries around restorations on bitewings using deep learning. J Dent. 2024 Feb; 143:104886.

[21] Lee S, Oh SI, Jo J, Kang S, Shin Y, Park JW. Deep learning for early dental caries detection in bitewing radiographs. Sci Rep. 2021 Aug;11(1):16807.

[22] Lian L, Zhu T, Zhu F, Zhu H. Deep Learning for Caries Detection and Classification. Diagnostics (Basel). 2021 Sep;11(9).

[23] Dashti M, Londono J, Ghasemi S, Zare N, Samman M, Ashi H, et al. Comparative analysis of deep learning algorithms for dental caries detection and prediction from radiographic images: a comprehensive umbrella review. PeerJ Comput Sci. 2024; 10:e2371.

[24] Mehdizadeh M, Estai M, Vignarajan J, Patel J, Granich J, Zaniovich M, et al. A Deep Learning-Based System for the Assessment of Dental Caries Using Colour Dental Photographs. Stud Health Technol Inform. 2024 Jan; 310:911–5.

[25] Sadr S, Rokhshad R, Daghighi Y, Golkar M, Tolooie Kheybari F, Gorjinejad F, et al. Deep learning for tooth identification and numbering on dental radiography: a systematic review and meta-analysis. Dentomaxillofac Radiol. 2024 Jan;53(1):5–21.

[26] Kamburoglu K, Kolsuz E, Murat S, Yüksel S, Ozen T. Proximal caries detection accuracy using intraoral bitewing radiography, extraoral bitewing radiography and panoramic radiography. Dentomaxillofac Radiol. 2012 Sep;41(6):450–9.

[27] Shearer AC, Wilson NH. Radiography for the diagnosis of dental caries in posterior teeth. Clin Prev Dent. 1989;11(1):24–8.

[28] Mosavat F, Ahmadi E, Amirfarhangi S, Rafeie N. Evaluation of diagnostic accuracy of CBCT and intraoral radiography for proximal caries detection in the presence of different dental restoration materials. BMC Oral Health. 2023 Jun;23(1):419.

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

[30] Kamburoglu K, Kolsuz E, Murat S, Yüksel S, Ozen T. Proximal caries detection accuracy using intraoral bitewing radiography, extraoral bitewing radiography and panoramic radiography. Dentomaxillofac Radiol. 2012 Sep;41(6):450–9.

[31] Nuvvula S, Bhumireddy JR, Kamatham R, Mallineni SK. Diagnostic accuracy of direct digital radiography and conventional radiography for proximal caries detection in primary teeth: A systematic review. J Indian Soc Pedod Prev Dent. 2016;34(4):300–5.

[32] Shearer AC, Wilson NH. Radiography for the diagnosis of dental caries in posterior teeth. Clin Prev Dent. 1989;11(1):24–8.

[33] Prabha AE, Packialakshmi A. Recent advances in caries risk assessment: A review. African Journal of Biomedical Research. 2024 Nov 28;27(3):133-41.

[34] Sivarajan M, Rakshagan V, Govindaraju L. Choice of Restorative Material by Dentists for Class I Caries in Second Mandibular Primary Molar in 3-6 Year Children Visiting a University Dental Hospital “A Retrospective Study. Journal of Advances in Medicine and Medical Research. 2024 Feb 1;36(1):105-14.

[35] Karthik V, Subramanian EM. Oral Hygiene Index in Children with Stainless Steel Crowns in the Permanent Molars. Asian Journal of Pediatric Research. 2024 Jan 29;14(2):6-13.