# Efficacy of Various Deep Learning Models for Automated Diagnosis in Oral and Maxillofacial Lesions

**Dr. K. R.Thenkkuzhali [1], Logeswari J [2], Baskaran Kuppusamy [3], Rajashri CK [4], Soundarya Kasi [5], Vasanthapriya J [6], Jeyaseelan R [7],**

[1] Department of Oral Medicine & Radiology, Sree Balaji Dental College and Hospital, Chennai, India krthenkkuzhali1999@gmail.com ORCID ID: 0009-0000-4743-1973

[2] Associate Professor, Department of Oral Pathology, Meenakshi Ammal Dental College and Hospital, Meenakshi Academy of Higher Education and Research. logeswari@maher.ac.in, ORCID: 0000-0002-2559-3119

[3]Scientist, Central Research Laboratory, Meenakshi Medical College Hospital & Research Institute, Meenakshi Academy of Higher Education and Research. baskark@maher.ac.in, ORCID: 0009-0003-5070-7450

[4]Assistant Professor, Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research. rajashrick@maher.ac.in, 0009-0007-9414-517X

[5]Meenakshi College of Pharmacy, Meenakshi Academy of Higher Education and Research. soundaryak@maher.ac.in, ORCID: 0009-0006-7648-3979

[6]Professor, Arulmigu Meenakshi College of Nursing, Meenakshi Academy of Higher Education and Research. vasantha@maher.ac.in, ORCID: 0000-0001-9953-9505

[7]Assistant Professor, Department of Oral Pathology, Meenakshi Ammal Dental College and Hospital, Meenakshi Academy of Higher Education and Research, Chennai, Tamil Nadu, India. 0000-0003-2722-3549jeyas@maher.ac.in

**ABSTRACT**

Recent advancements in deep learning (DL) have significantly enhanced automated diagnostic capabilities in oral and maxillofacial radiology. Convolutional neural networks (CNNs) and their variants, such as YOLO, U-Net, Mask R-CNN, and hybrid CNN–Transformer architectures, have demonstrated superior accuracy in detecting, segmenting, and classifying lesions in panoramic, periapical, and CBCT images. These models improve clinical workflows by enabling rapid interpretation, reducing observer variability, and ensuring consistent precision in identifying caries, cysts, and neoplastic lesions. YOLO models facilitate real-time object detection, U-Net variants deliver detailed segmentation, and Mask R-CNN allows instance-level delineation. Emerging CNN–Transformer hybrids combine contextual and spatial reasoning, leading to robust diagnostic performance. Overall, DL-based image analysis provides a reliable adjunct to clinical decision-making, advancing precision-driven dental radiology.

**Keywords:** *Deep learning, oral and maxillofacial radiology, artificial intelligence.*

## INTRODUCTION

In dentistry, AI has found applications across several domains, including prosthodontics, customized computer-aided design and production of orthodontic and surgical equipment, oral cancer detection, implantology, periodontal disease management, endodontics, and cariology.[1]Three key issues have been addressed by Deep learning, a sophisticated kind of machine learning: segmentation, detection, and classification.[1] Artificial intelligence (AI) has made considerable advancements in the field of ST detection.[2]Machine learning (ML) is a subfield of artificial intelligence (AI) that is dedicated to developing algorithms capable of "learning" statistical patterns in data, with the ultimate goal of predicting previously unobserved data.

Deep Learning (DL) is a subset of ML that is based on multi-layer artificial neural networks (ANN). Deep neural networks are particularly helpful for tasks involving vision and large datasets. Often, DL methods excel ML approaches at image segmentation, classification, and detection.[3] Segmentation of high-resolution cone-beam computed tomography (CBCT) images plays a crucial role in developing three-dimensional (3D) models in the diagnosis and treatment planning for individuals with craniomaxillofacial (CMF) abnormalities.[4]Periapical radiographs demonstrate improved accuracy in detecting bone defects and marginal bone levels due to their comprehensive imaging, making them suitable for measuring furcation involvement, but they need numerous exposures for more extensive coverage for long-term monitoring of severe bone alterations.[5] Artificial intelligence (AI) has enhanced radiodiagnosis in oral radiology by addressing the inaccuracy of manual measurements.[5]AI can act as an automated diagnostic assistance system, eliminating human error, delivering more accurate information, and preventing misdiagnosis caused by inexperience or weariness. Additionally, AI boosts efficiency, decreases costs, and enables faster medical data processing.[5] The fundamental drawback of conventional radiography resides in its 2D portrayal of caries lesions, which are intrinsically 3D structures. This 2D constraint might result in the loss of vital information, making it tougher to estimate the entire extent of the caries. on other side CBCT greatly increases the identification of tooth root canal spaces and periapical regions but not especially developed for diagnosing dental caries. The accuracy, sensitivity, specificity, and classification capabilities of CBCT image processing have been greatly enhanced by recent developments in deep learning.[6] There are significant difficulties with traditional dental segmentation methods that call on human intervention, such as manually choosing tooth border markers or annotating a small number of surface points.[7] Deep learning's capacity to learn complex patterns and features from vast datasets offers enormous potential to overcome the limits of traditional approaches and push the frontiers of dental imaging accuracy and efficiency.[7] Analyzing X-rays is not only time-consuming but also requires a trained dentist and is subject to human error, potentially leading to inaccurate diagnosis and treatment recommendations. [8].Images used in dentistry are now frequently digitized and readily converted into computer language. Therefore, the application of AI in the supplementary detection of dental problems seems promising.[9]

## DEEP LANGUAGE MODELS AND MECHANISMS

### YOLOv5 and YOLOv8

The YOLO (You Only Look Once) family adopts a single-stage object detection strategy that divides input images into grids, simultaneously predicting bounding boxes and class probabilities [1]. With improvements in computer vision, the YOLO (You Only Look Once) series has become a potent tool for object recognition ,renowned for its speed and accuracy. [2] Pornprasertsuk -Damrongsri et al. applied YOLOv5 for multistage caries detection in panoramic radiographs, achieving high diagnostic sensitivity and fast processing, making it suitable for clinical use [1]. Specifically, the YOLOv5s architecture with over 7.2 million parameters was used. This model was trained on the big public dataset dubbed "DENTEX CHALLENGE 2023". according to Pornprasertsuk -Damrongsri et al the efficacy of the trained YOLOv5s model in recognizing tooth regions with precision of 99.6%, a recall of 98.9%, a mean average precision (mAP) of 99.5% at mAP50, and 79.9% at mAP .[1]

YOLOv8 outperformed in real-time detection by displaying stronger recall and more consistent performance across multiple thresholds, making it especially well-suited for scenarios demanding a compromise between precision and recall.[2]YOLOv8 excels at real-time detection and segmentation.[2]YOLOv8 has a modest edge in flexibility and peak accuracy, making it more suited for real-time applications. YOLOv8 has an accuracy of 0.9883 and a recall of 0.8230 .[2] Since its debut in 2015 , Using YOLOv1,the series has consistently developed, making it ideal for real-time applications. YOLOv8 further optimizes detection by processing the entire picture in one pass, combining quicker speeds with greater accuracy and economy. Its innovative architecture and anchor-free design increase feature extraction and detection performance while needing less computing resources compared to multi-stage detectors. It offers a major benefit in supernumerary diagnosis due to its capacity to generalize across various imaging circumstances and dental defects.[2]While YOLO systems enable real-time diagnostics, they are less suited for pixel-level segmentation tasks.

### *U-Net, nnU-Net, and BDU-Net*

U-Net is a breakthrough and has evolved to a commonly used benchmark in various segmentation challenges.[4] The 3D Regions of Interest (RoI)-aware U-Net (3D RU-Net) consists of a global image encoder and a GPU memory-efficient local decoder, performing a global-to-local multi-task learning procedure for joint RoI localization and in-region segmentation where the two tasks share one backbone encoder network. Voxel Rend-based U-Net (VR-U-Net) combines a voxel-based rendering (Voxel Rend) module for high-resolution volumetric segmentation with a GPU memory-efficient version of 3D U-Net. A modular, lightweight neural network developed from Point Rend, the Voxel Rend module offers effective voxel-wise predictions at troublesome voxel positions. Using a high-resolution CMF CBCT dataset, the recommended VR-U-Net was tested in the segmentation of multi-class bone structures [4]. The Mesh U-Net achieved 94.87% accuracy for tooth segmentation and 83.32% accuracy for caries detection.[7] It was reported that training nnU-Net on complete high-resolution dental X-ray pictures (1024 × 512) gave a Dice score of 90.68% and an IoU of 83.44% — much better than when using lower-resolution images. When they utilized a "patched" technique (splitting the high-res picture into overlapping 256 × 256 patches with a slight stride), performance increased further: patched nnU-Net obtained a Dice of 91.32% and IoU of 84.12%, exceeding the whole-image model.[8] Two sub-networks make up the majority of BDU-Net. One is the area sub-network used to create the region segmentation findings, while the other is the border sub-network that changes the segmentation borders.

The findings of sensitivity and specificity were 0.863 and 0.983 for identifying missing teeth, 0.821 and 0.989 for diagnosing caries, 0.718 and 0.997 for diagnosing residual roots, 0.942 and 0.986 for diagnosing impacted teeth, and 0.835 and 0.991 for diagnosing entire crowns.[9]

***Faster R -CNN and Mask R-CNN***

CNN-based volumetric segmentation generally demands vast memory of graphics processing units (GPUs) to analyze a big picture-size dataset (e.g., millions of voxels)[4]. The most popular method for identifying RBL and categorizing periodontitis in panoramic radiographs is deep convolutional neural networks (CNNs). [5]In dentistry, CNNs are utilized for image segmentation, detection, categorization, and quality enhancement. CNNs, in particular, regional models like Faster R-CNN and Mask R-CNN, have effectively segmented radiographs for periodontitis detection[5]Dense Net is a CNN design that connects all layers feed-forwardly, unlike traditional networks that connect just successive levels.[5]Faster R-CNN(Region-based Convolutional Neural Network)has proven itself as a core model in the application of AI for diagnosing periapical radiography.[2]

Faster R CNN's two-stage approach—region suggestion followed by classification—has proved helpful in addressing the complexity of dental radiographs[2] Faster R-CNN, although having good precision at low recall values, has a notable reduction in precision as recall grows. Faster R-CNN was not suited for real-time applications because to its slower speed . Faster R CNN, but less flexible, gave dependable performance for detailed diagnostic tasks.[2]Periodontitis in panoramic radiographs may be successfully segmented using the Mask R-CNN instance segmentation model.[5] The Mask R-CNN technique was created to identify targets in pictures and produce high-quality segmentation results based on Faster R-CNN . Recently, Mask R-CNN has been employed in different applications, such as target extraction , pathological cell identification , and crop identification . It has also been applied in more specific fields, like dental pathology, for illnesses including herpes labialis, aphthous ulcers , and periapical pathosis, helping to locate responsible tooth[6] Mask R-CNN has become increasingly used in CBCT image analysis for tasks like dental abnormality identification due to its capacity to do exact pixel-level segmentation. However, there are a number of issues with using Mask R-CNN on CBCT images, including low resolution, picture noise, and the intricacy of dental structures, which can have an impact on model performance.[6] It was reported that utilizing transfer learning with COCO-pretrained weights (the "C-group") for Mask R-CNN produced a mean average precision (mAP) of ~ 81.095% for tooth detection in CBCT images. For caries (decay) detection, the performance remained low, indicating that while Mask R-CNN shows promise for tooth identification, automatic caries detection in CBCT still needs substantial improvement.[6]

**Hybrid two-stage CNN model**

The segmentation training uses the Mask R-CNN model, built using the Detectron2 framework with a Residual Networks 101 (ResNet101) backbone. In this phase, Mask R-CNN was trained to carry out three automated segmentation tasks: RBL, CEJ, and tooth segmentation. Following this, the staging training using DenseNet169 to train the Two-Stage CNN model for classifying (stage) periodontitis in panoramic radiographs.[5] The model demonstrates robust performance across all assessment metrics—including precision, recall (sensitivity), specificity, F1-score, and accuracy.[5]The higher True Positive (TP) values for stage 3 and 4 periodontitis detection show that the Two-Stage CNN consistently does a good job of identifying and categorizing these conditions. The Two-Stage CNN performs poorly in detecting early-stage periodontitis (stages 1 and 2), indicating a need for additional tuning. [5]The final testing outputs indicate the average precision, recall (sensitivity), specificity, F1-score, and accuracy values across all prediction classes of 0.59, 0.51, 0.88, 0.53, and 0.80, respectively. [5]The model had its best performance in periodontitis staging for specificity (0.88) and accuracy (0.80).[5]

## DISCUSSION

Precise localization and distinction of caries phases (enamel, dentine, and pulp) are made possible by the employment of a two-model architecture: YOLO for tooth detection and Attention U-Net for caries segmentation.[1] This degree of clinical validation and detail is uncommon in earlier research. The model also achieves great recall (0.96), indicating its focus on avoiding missed diagnoses, which is crucial in clinical settings.[1]A CNN was able to reliably identify and characterize cystic lesions in CBCT images whereas a YoloV5x-based model effectively anticipated the surgical difficulties of impacted maxillary third molars from panoramic radiography.[2] YOLOv8 keeps its precision at 1.0 up to a recall of roughly0.8, but Faster R-CNN, although having great accuracy at low recall values, experiences a noticeable drop in precision as recall increases.[2] Faster R-CNN's slower speed made it unsuitable for real-time applications, whereas YOLOv8 performs better in real-time detection and segmentation but has a larger recall.[2] The YOLOv8 curve consistently performs better than the Faster R-CNN curve, suggesting that YOLOv8 achieves superior accuracy at all recall levels.[2]VR-U-Net achieved higher segmentation accuracy than the 3D U-Net using only half of the memory consumption compared with that of 3D U-Net. The network found integrates a GPU memory-efficient variant .[4]A 3D U-Net with a Voxel Rend module that conducts voxel-based predictions on adaptively selected regions.[4]The runtime of a deep learning model is a significant aspect for clinical application, as it effects the efficiency and viability of the model when deployed by clinicians.[5] A model with a shorter runtime can help radiologists and physicians with manual radiodiagnosis procedures and increase time efficiency.[5] CNN models are the predominant deep learning type employed in AI-related oral radiology research, suggesting their superiority in the processing of medical images.[5] Mask R - CNN performance is lower to other CNN models, such as Multi-Label U-Net, developed for semantic seg mentation.[5] Mask R-CNN expands on Faster R-CNN by incorporating pixel-level mask prediction with RoIAlign, which improves alignment for more accurate results. It also includes a dual-task technique with a mask loss function, boosting both identification accuracy and processing speed, making it a strong tool in computer vision.[6] Mask R-CNN gives excellent segmentation accuracy but is slower than You Only Look Once (YOLO) , which is more suited for real-time detection, but it may compromise some precision. Mask R-CNN is better than Faster R-CNN and YOLO for jobs requiring pixel-level segmentation, including lesion border detection. Conversely, applications requiring the quick recognition of many objects are better suited for faster R-CNN and YOLO.[6] These jobs can also be handled using Mask R-CNN, despite its greater complexity.[6] Ultimately, the decision between these models relies on whether speed or accuracy is valued, and a comparative evaluation can assist decide the most acceptable alternative for a certain use case.[6] Semantic segmentation performance is greatly enhanced by using patch-based techniques with overlapping areas and training nnU-Net with higher-resolution pictures.[8] nnU-Net can automatically adapt to any dataset by adjusting the hyperparameters according to the data characteristics . BDU-Net focuses on enhanced generalization capabilities and instance boundary adjustment, improving not only the accuracy of tooth position identification, but also achieving more accurate segmentation results.[9] It is common knowledge that CNNs' internal operations and decision-making procedures are still opaque and challenging to comprehend, which is why they are referred to as "black boxes." Grad-CAM was utilized to make the CNN-based model more apparent through visual explanations where It emphasizes the regions in an input picture that are significant for the prediction of a given class.[10] Yolov5, as a one-stage object detection technique, delivers fast detection, making it well-suited for quickly screening huge volumes of periapical radiographs. Moreover, it demonstrates remarkable tolerance to scale fluctuations and occlusions, enabling effective identification of periapical lesions even in complicated backgrounds. So , ConvNeXt is a novel deep learning model for image categorization which combines the conventional benefits of CNNs with the newest breakthroughs in Transformer models for visual applications, yielding improved efficiency and accuracy.[11] Artificial intelligence-based clinical decision support systems can interpret diverse types of data with powerful machine learning and deep learning algorithms. However, despite its technological potential, AI-CDSS for OC remains experimental, and clinical validation and real-world value have yet to be shown.[12] Using a smartphone to apply the CNN approach might be beneficial for remote dentistry or for evaluating lesions prior to consultation or expert reference. In the future, a comprehensive clinical assessment and history-taking mixed with the employment of AI technologies and CNN as diagnostic tools may be applied to diagnose illnesses.[13] .The major benefit of deep learning is that these layers of characteristics are learnt directly from raw data using an overall learning process, rather than being developed by human engineers and depending entirely on dentist’s trained eyes. [14]To assist professionals in making a more accurate diagnosis, computational technologies have been made available as decision-supporting aids. Also, these deep learning algorithms have shown promising outcomes in diagnosing oral cancer related disorders successfully utilizing computer aided cancer detection and medical pictures.[14]

## LIMITATIONS

One of the key limitations is the quality and quantity of data available for training AI models. High-quality, labeled datasets are crucial for training efficient and accurate AI algorithms, but preparing such datasets may be time-consuming and demanding .[15]The ’black box’ character of many AI algorithms can be troublesome. The inability to grasp how these algorithms arrive at a given outcome might lead to skepticism and hesitation in their adoption. [15]

This issue is further exacerbated by ethical and regulatory concerns involving patient data privacy, informed con sent, and responsibility in the case of AI-induced failures . [15] The sample strength used in each study is another drawback. The amount of the dataset used to train and assess an AI model can considerably effect its performance and generalizability. AI models trained on tiny datasets may not perform as well when applied to fresh data, limiting their applicability in real world clinical situations. Additionally, the quality, avail ability, and consistency of the data employed in these investigations pose considerable issues. For instance, the quality of diagnostic imaging for head and neck cancer management , radiographic imagery for oral cancer diagnosis , or CBCT pictures for detecting missing teeth’s positions can considerably impact the AI model’s
efficacy. Inconsistent or poor-quality data might lead to inaccurate forecasts or diagnosis.[15]

## FUTURE ASPECTS

Collaboration across healthcare organizations to exchange and compile data in a safe, privacy-compliant way can help with data-related concerns. The development of more interpretable AI models, or providing some type of decision-making knowledge, can assist mitigate the 'black box' issue.[15] Dental clinics will feature AI Comprehensive Care system in future where the prior appointment the AL patient history analyzer will review intended treatment plan according to age , gender , medical history and past dental history .This can be used before , after the dental procedures for future treatment plans [16].

## CONCLUSION

Deep learning has demonstrated strong efficacy in automating diagnosis of oral and maxillofacial lesions, ensuring reproducible accuracy and efficiency. Proper usage by the dentist is required for daily practice of several AI tools in diagnosing and treatment of oral disease , AI can be used as adjuvant to human diagnosis and can never be the only modalities for identifying or any procedure in medical field.

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