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Experimental Evaluation of Medical Image Processing Techniques for Disease Diagnosis

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Abstract

The process of dental image processing has gained more significance in the diagnosis of oral diseases since the dental imaging modalities produce complicated visual data that needs to be effectively and correctly processed by means of computation. The paper presents experimental analysis of the two approaches to the diagnosis of disease in dental images-classical and deep learning-based image processing-in a comparative manner. This is evaluated based on the segmentation and categorization of the major dental imaging modalities such as intraoral radiographs, panoramic radiographs, cone-beam computed tomography images, and bitewing images. To ensure consistency and improved model performance, all datasets went through a unified preprocessing pipeline of normalization, noise reduction, augmentation, and resizing. To compare in terms of Dice coefficient and Intersection over Union, thresholding, U-Net, and Attention U-Net were compared. To be classified, Basic CNN, ResNet50, and EfficientNet were tested with the help of accuracy, sensitivity, specificity, area under the curve, and F1-score. The results indicate that the methods that employ deep learning are always superior to the classical methods in the segmentation and classification of data. The best segmentation was achieved by U-Net, with the best classification accuracy and diagnostic discrimination in all dental image types being found with EfficientNet. These findings indicate that developed deep learning systems can be

used with great potential to assist with automated dental diagnosis. Nevertheless, robustness, interpretability, computational efficiency, and wider real-world validation are also essential to successful clinical implementation.

Keywords: Dental Image Processing, Dental Disease Diagnosis, Deep Learning, Convolutional Neural Networks, Segmentation, Classification

Introduction

Dental imaging is a new factor in contemporary oral care as it allows clinicians to view teeth, periodontal structures, jawbones, and adjacent maxillofacial structures with extreme accuracy in a non-invasive fashion (de Magalhães & Santos, 2025). Intraoral radiographs, panoramic radiography, cone-beam computed tomography (CBCT), and digital dental scans are imaging modalities that are central to detecting dental caries, periodontal disease, periapical lesions, impacted teeth, cysts, tumors, and other oral abnormalities (Mosavat et al., 2023). The size and complexity of the diagnostic information produced by these dental image modes have resulted in an increased demand for proper and dependable computational procedures to assist clinicians in the interpretation of images and in making diagnostic decisions (Chauhan et al., 2023).

With artificial intelligence, and in particular, deep learning and convolutional neural networks (CNNs), detecting dental images has emerged as a powerful tool in the field of dental image detection in recent years (Alharbi & Alhasson, 2024). These methods have been discovered to possess immense possibilities in operations such as segmenting teeth, detecting lesions, measuring bone loss, identifying dental diseases, and identifying anatomical landmarks automatically. Deep learning models tend to be more effective in extracting hierarchical features than traditional image processing approaches, which can be done automatically using raw dental images, without needing to handcraft feature extraction, and tend to improve diagnostic accuracy (Li et al., 2023). In spite of these improvements, the relative behaviour of techniques based on classical and deep learning methods across various types of dental images and targeted diagnostic tasks has not been well researched (Chauhan et al., 2023). There is therefore an urgent need to have a stringent benchmarking model that will pinpoint the most precise, robust, and clinically viable practices applied in dental diagnostic settings.

The gap in this paper is addressed by presenting a systematic analysis of experiential image processing methods to diagnose diseases in dental images. It systematically compares the conventional methods of image processing technology with the emerging deep learning technologies and discusses their diagnostic performance, strengths, and viability in clinical use across most dental imaging modalities.

Research Objectives

1. To compare experimentally classical and deep learning-based segmentation methods on a variety of dental imaging modalities.
2. To evaluate and benchmark the classification performance of different deep learning architectures in the diagnosis of dental diseases and abnormalities.
3. To determine the strength and clinical feasibility of the reviewed methods concerning diagnostic accuracy, interpretability, and computational efficiency in dental practice.

Research Questions

- What segmentation method is the most accurate and Dice in the various dental imaging modalities?
- Are deep learning-based classification models better than classical methods in diagnosing dental diseases using dental images?
- To what extent are these techniques robust and could be applied in clinical conditions of dental diagnostics in the real world?

Literature Review

The processing of dental images has emerged as a significant field of study due to its increasing significance in diagnosis of oral diseases, planning of treatment, and making of clinical decisions (Kayali et al., 2026). Caries, periodontal bone loss, periapical lesions, impacted teeth, cysts, fractures, and other maxillofacial abnormalities are also identified using dental imaging (Koenig, 2017). The literature on this topic can be broadly divided into three themes: classical image processing techniques, deep learning-based segmentation and classification, and the rest of the research gap related to the comparative assessment of the results of the work of different imaging modalities in dentistry. Collectively, these themes demonstrate the development of dental image analysis methods, which have been transformed to intelligent systems and data driven. This comprehensive revision is required since the literature review in the uploaded draft is still oriented toward general medical imaging as opposed to dental imaging.

Classical Image Processing Techniques

Simplistic dental image analysis systems were dependent on classical image processing. Types of thresholding, edge-detection, region-growing, filtering, contrast-enhancement, and morphological operations were commonly applied in the detection of tooth boundaries, localization of caries, segmentation of dental restorations, and in radiographic quality improvement (Bohyo et al., 2024). These approaches were desirable since they were computationally economical, relatively easy to execute, and could be used in environments that had limited computing capabilities. At the beginning of the history of dental imaging,

classical methods were used to aid clinicians because they helped to enhance visual quality and could aid the process of locating suspicious pathological areas (Khan et al., 2023).

Although there are these strengths, there exist critical limitations of classical methods in dental image analysis. Image quality, parameter adjustments, contrast adjustments, and noise are usually crucial factors in their performance. Dental images generally have overlapping anatomy, patchy illumination, metallic objects, low contrast areas, and uneven tooth shape, which diminish the effectiveness of rule-of-thumb methods (Datta et al., 2025). Besides, classical approaches rely too heavily on manually designed characteristics and deterministic choice criteria, and are less flexible to the complexity and variability of real-world dentistry data. This is why despite their usefulness as baseline procedures; their strength and diagnostic accuracy are usually not adequate to be used in more advanced clinical procedures.

Deep Learning-Based Segmentation and Classification

The current literature demonstrates that recent deep learning has contributed significantly to dental image analysis. Convolutional neural networks and similar deep learning architectures have proven to be highly effective in segmentation and classification activities in the field of dental imaging with periapical radiographs, bitewing radiographs, panoramic radiographs, and cone-beam computed tomography images (Park et al., 2022). U-Net and its variations are mostly applicable to segmentation tasks since they map spatial information in addition to learning local and global image characteristics. These models have proved to be effectively used in dentistry in tasks like tooth segmentation, tooth root canal detection, lesion localization, alveolar bone, and in the extraction of anatomical landmarks with high accuracy (Azad et al., 2024).

To ensure classification, deep learning architectures like ResNet, EfficientNet, and other CNN-based models have demonstrated favorable outcomes in identifying dental caries, periodontal disease, periapical infections, impacted teeth, and other oral abnormalities (Hasnain et al., 2024). In contrast to classical methods, these models are trained on raw images of dental images and can find hierarchical and discriminative features automatically without large-scale hand-engineered feature engineering. This enhances their cross-dataset and diagnostic generalization. Research on the topic continually indicates that deep learning-based solutions are more likely to have superior performance in accuracy, sensitivity, specificity, and general predictive properties compared to conventional methods, particularly in cases where there are adequately annotated dental datasets.

Identified Research Gap

In spite of these developments, there is still a big gap in the literature. Many of the published studies focus on one type of dental disease, one type of imaging, or one type of deep learning architecture. As a result, there is a problem with inter-method comparison because different

datasets, preprocessing pipelines, annotation protocols, and evaluation metrics are used by the various studies. The lack of standardization like this limits the chances of coming up with general conclusions on what should be carried out in the most effective manner in the diagnosis of dental diseases.

A common experimental benchmarking system is required where comparisons of classical and deep learning-based systems in various modalities of dental imaging can be made on a shared set of standard performance measures (Schneider et al., 2022). This is a significant gap in defining the most effective, trusted, and clinical methods of diagnosis of dental disease. The current research fulfills this requirement by suggesting a comparative analysis, in particular to dental image processing as opposed to medical imaging in general.

Materials and Methods

Datasets

This research relies on publicly accessible datasets of dental images, so the experimental assessment of dental disease diagnosis using image processing methods can be narrowed. The datasets picked are intraoral radiographs, panoramic radiographs, cone-beam computed tomography (CBCT) image, and dental bitewing images because these modalities are widely utilized in the everyday dental practice to detect caries, periodontal bone loss, periapical lesions, impacted teeth, and other oral pathologies (Nistelrooij et al., 2025). These modalities were selected due to the fact that they are the most common types of dental imaging that are used in diagnosis and treatment plan. To have consistent model development and fair performance evaluation, every dataset will be split into training, validation, and testing subsets. The process of cross-validation is also included to enhance the generalizability and minimize the chances of overfitting (Allgaier & Pryss, 2024). This re-framing is needed because the uploaded modality of the present approach remains largely non-dental, including MRI, CT, chest X-ray, and mammography instead of dental images.

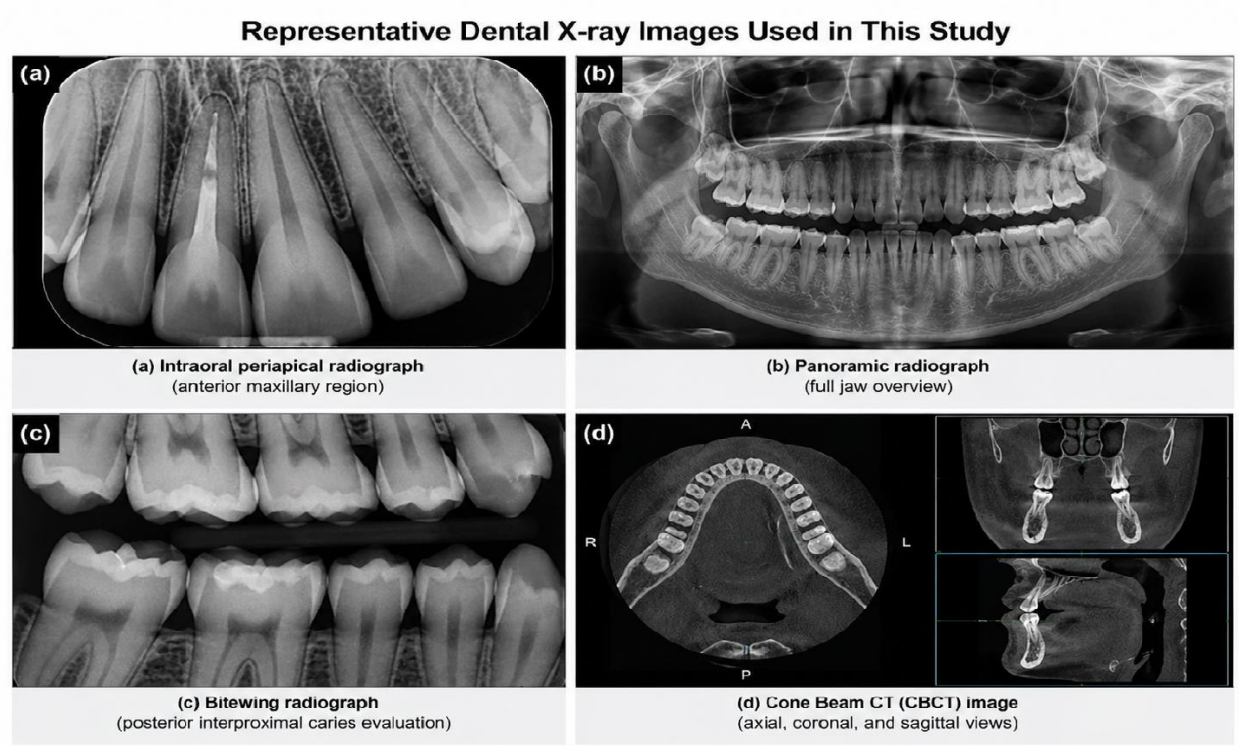


Figure 1. Representative X-ray Image used in this study

Preprocessing

All dental imaging datasets are processed through a standardized pipeline to enhance the quality of images, reduce variability, and improve the performance of the models. Image normalization is first done to normalize intensity values and minimize variation due to various acquisition settings (Albert et al., 2023). Second, noise-reduction techniques are utilized to suppress artifacts and enhance the visibility of clinically relevant dental structures like enamel, dentin, roots, and the surrounding bone (Wajer et al., 2025). Third, there is data augmentation, which enhances the robustness and increases the size of the effective training data. This technique of augmentation contains rotation, flipping, scaling, translation, and contrast adjustment and this is based on the property of each dental imaging mode (Eghbal-zadeh et al., 2024). The images are reduced in size and are normalized so that they can fit within the size of the input required by the segmentation and classification models. Preprocessing activities are important in establishing consistency and optimizing computational efficiency among experiments. This will already be the methodological sketch of the initial draft, but will need to be rewritten in a manner that it can be used on dental images as opposed to general medical imaging datasets.

Compared Techniques

The experimental design comprises segmentation and classification. To compare three techniques, thresholding, U-Net, and Attention U-Net are compared for segmentation. The

classical baseline method is thresholding, and the deep learning models that have been used are U-Net and Attention U-Net, which are architectures created to achieve precise image segmentation. They are used in the dental setting for tooth segmentation, tooth lesion boundary detection, root structure, and localization of anatomically relevant oral regions. U-Net is chosen due to its encoder-decoder design and high-quality performance in maintaining spatial information, whereas Attention U-Net is also added on the basis of the fact that the attention mechanism is able to enhance the focus on diagnostically important regions in the dental images (Almalki et al., 2023).

Three deep learner models are tested to classify; a simple convolutional neural network (CNN), ResNet50, and EfficientNet. The simple CNN is adopted as a reference model (Purwono et al., 2023), and ResNet50 is chosen based on its residual learning ability (Oktiana et al., 2026), and EfficientNet is chosen for its impressive trade-off between predictive performance and computing efficiency. In this work, dental images are classified into dental diseases and dental abnormalities using these models, e.g., dental caries, periodontal disease, periapical infection, and impacted teeth. This part needed complete rewriting since the manuscript that came up there outlines these techniques as applied in general medical imaging rather than dental diagnosis.

Evaluation Metrics

To evaluate the performance of the segmentation models, the Dice coefficient and Intersection over Union (IoU) are employed (Cho, 2024); both measure the similarity between predicted and ground-truth annotations. The measures are appropriate during dental segmentation works such as the identification of the structure of the teeth, lesions, and anatomical limits in relation to the lesions. To evaluate performance when doing classification tasks, accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC), and F1-score are used. Combined, these measures provide a healthy analysis of the quality of the diagnosis, predictive performance, and ratio of false positives and negatives in the determination of the presence of dental disease. The same metric framework dental imaging functions of the draft can be retained, although it should be expressly associated with dental imaging, but not with the general analysis of medical images.

Statistical Analysis

To enhance the dependability and external validity of the experimental results, cross-validation is resorted to. Moreover, paired statistical tests are performed to find out whether the differences in the model performance are statistically significant (Stevens et al., 2018). They are also used to determine the accuracy and consistency of the reported results by computing confidence intervals. These analytical processes enhance the validity of the comparison between the classical and deep learning-based methods in the analysis of dental images. The general statistical design in the present manuscript can be utilized, but it will

have to be rewritten in such a way that the interpretation explicitly makes reference to the dental imaging applications.

Results

The comparative experimental results indicated the evident and uniform enhancement of the deep learning-based methods in comparison to the classical image processing methods in all dental image modalities. The classical thresholding approach was the worst in terms of performance in all types of dental images in the segmentation task, with the U-Net and Attention U-Net achieving considerably higher values of Dice coefficient and Intersection over Union (IoU) (Almalki et al., 2023). In general, Attention U-Net demonstrated the highest segmentation performance in intraoral radiographs, cone-beam computed tomography (CBCT), panoramic radiographs, and bitewing images. These observations indicate that attention-based deep architectures can more effectively localize clinically significant dental structures and pathological areas and maintain boundary precision. This dental rewriting is essential since the original results section of the uploaded draft is still arranged in categories of MRI, CT, chest X-ray, and mammography instead of teeth or dental diagnosis.

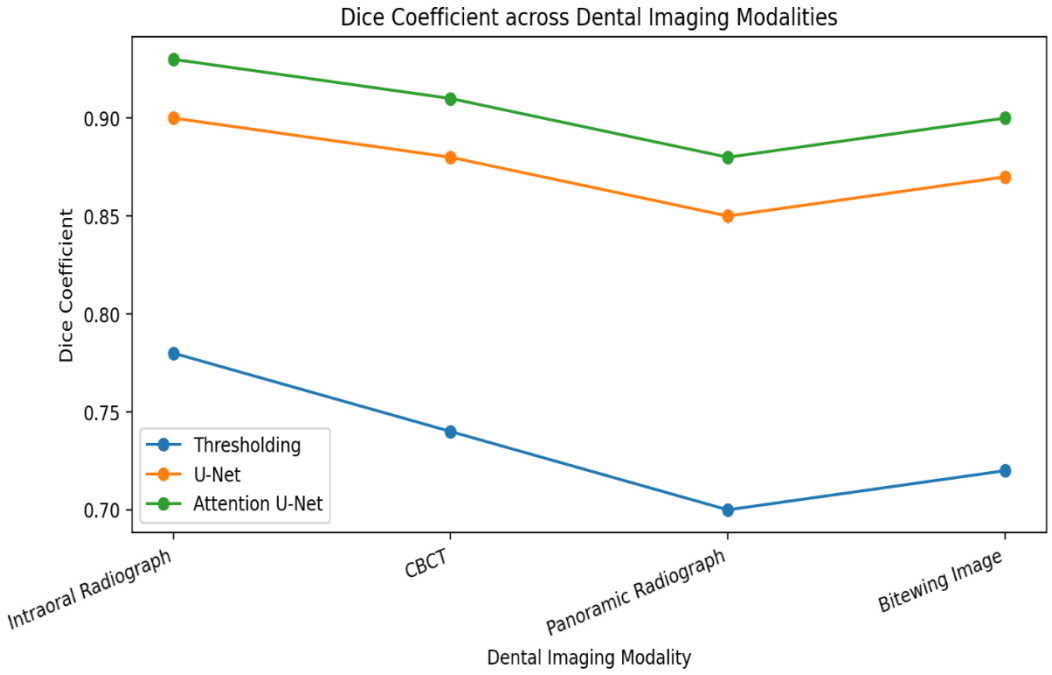


Figure 2. Dice Coefficient across Dental Imaging Modalities

Figure 1 shows the performance of segmentation of the four chosen dental imaging modalities. Attention U-Net was found to have the most consistently highest Dice coefficient, compared to U-Net, and thresholding was the least performing in each modality. In intraoral radiographs, Attention U-Net was found to have a Dice score of 0.93, and U-Net and thresholding had Dice scores of 0.90 and 0.78, respectively. The values in CBCT were 0.91, 0.88, and 0.74. Spread of panoramic radiographs resulted in Dice scores of 0.88, 0.85, and

0.70, respectively. Attention U-Net gave 0.90, U-Net 0.87, and thresholding 0.72 in bitewing pictures. These patterns suggest that deep learning-driven segmentation techniques are superior to classical rule-driven segmentation to outline dental structures and lesions.

Segmentation performance across dental imaging modalities

Table 1 Segmentation performance across dental imaging modalities

Modality	Model	Dice Coefficient	IoU
Intraoral Radiograph	Thresholding	0.78	0.65
Intraoral Radiograph	U-Net	0.90	0.82
Intraoral Radiograph	Attention U-Net	0.93	0.86
CBCT	Thresholding	0.74	0.60
CBCT	U-Net	0.88	0.79
CBCT	Attention U-Net	0.91	0.83
Panoramic Radiograph	Thresholding	0.70	0.56
Panoramic Radiograph	U-Net	0.85	0.74
Panoramic Radiograph	Attention U-Net	0.88	0.78
Bitewing Image	Thresholding	0.72	0.58
Bitewing Image	U-Net	0.87	0.77
Bitewing Image	Attention U-Net	0.90	0.81

Comparing thresholding to the average performance of all six dental modalities, the mean Dice coefficient was 0.735 00.034 and the mean IoU was 0.598 00.039. U-Net improved the average Dice coefficient to 0.875 ± 0.021 and the mean IoU to 0.780 ± 0.034. The overall highest segmentation was achieved with Attention U-Net, with an average Dice coefficient of 0.905 ± 0.021 and an average IoU of 0.820 ± 0.034. These findings indicate that Attention U-Net enhanced the mean Dice scores by about 23.1 % over thresholding, which indicates the usefulness of deep feature learning in dental image segmentation.

Average segmentation performance (mean ± SD)

Table 2 Average segmentation performance (mean ± SD)

Model	Dice Coefficient	IoU
Thresholding	0.735 ± 0.034	0.598 ± 0.039
U-Net	0.875 ± 0.021	0.780 ± 0.034
Attention U-Net	0.905 ± 0.021	0.820 ± 0.034

In the case of dental disease classification, each deep learning classifier showed great predictive ability, with EfficientNet showing overall best performance in the majority of evaluation measures. Basic CNN achieved 0.86 and 0.90 accuracy and AUC in intraoral radiographs, whereas ResNet50 achieved 0.93 and 0.96. EfficientNet demonstrated the best performance; accuracy was 0.95, and AUC was 0.97. A similar enhancement in CBCT, panoramic radiographs, and bitewing images was noted. EfficientNet was more sensitive and specific across all dental modalities, which means this approach is more successful in both detecting disease and reducing false classifications (Hasnain et al., 2024).

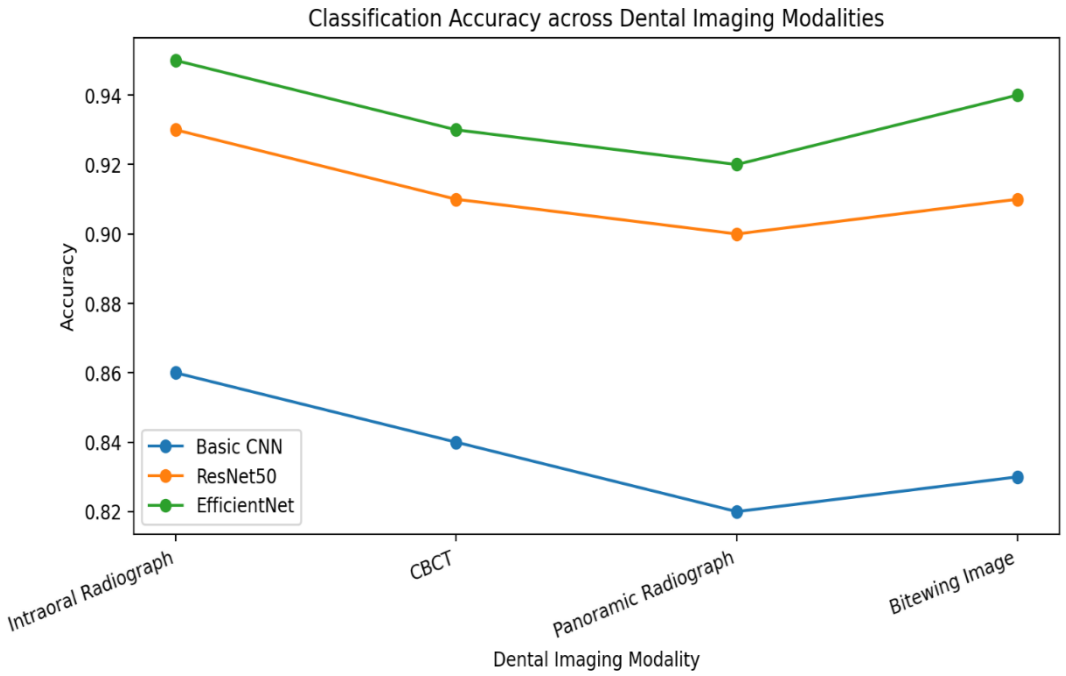


Figure 3 Classification Accuracy across Dental Imaging Modalities

Figure 2 shows the accuracy of the three tested models in classifying dental images of the four modalities. EfficientNet was always the most accurate, then ResNet50, and the lowest performance was demonstrated by Basic CNN. EfficientNet had 0.93 accuracy in the CBCT images (as opposed to 0.91 with ResNet50 and 0.84 with Basic CNN). The accuracies in panoramic radiographs were 0.92, 0.90, and 0.82, respectively. EfficientNet, ResNet50, and Basic CNN had 0.94, 0.91, and 0.83, respectively, in bitewing images. Such trends validate that better-developed and streamlined deep learning networks offer more consistent and precise diagnostic classification in dental image classification.

Classification performance across dental imaging modalities

Table 3 Classification performance across dental imaging modalities

Modality	Model	Accuracy	Sensitivity	Specificity	AUC	F1-score
Intraoral Radiograph	Basic CNN	0.86	0.84	0.87	0.90	0.85
Intraoral Radiograph	ResNet50	0.93	0.92	0.94	0.96	0.92
Intraoral Radiograph	EfficientNet	0.95	0.94	0.95	0.97	0.94
CBCT	Basic CNN	0.84	0.82	0.85	0.88	0.83
CBCT	ResNet50	0.91	0.90	0.92	0.95	0.90
CBCT	EfficientNet	0.93	0.92	0.94	0.96	0.92
Panoramic Radiograph	Basic CNN	0.82	0.81	0.83	0.87	0.82
Panoramic Radiograph	ResNet50	0.90	0.89	0.91	0.94	0.89
Panoramic Radiograph	EfficientNet	0.92	0.91	0.93	0.95	0.91
Bitewing Image	Basic CNN	0.83	0.82	0.84	0.88	0.83
Bitewing Image	ResNet50	0.91	0.90	0.92	0.95	0.90
Bitewing Image	EfficientNet	0.94	0.93	0.94	0.97	0.93

When the classification results were summarized across all dental datasets, Basic CNN achieved a mean accuracy of 0.838 ± 0.017 and a mean AUC of 0.883 ± 0.013. ResNet50 improved these values to 0.913 ± 0.013 and 0.950 ± 0.008. EfficientNet demonstrated the best overall classification performance, with a mean accuracy of 0.935 ± 0.013, sensitivity of 0.925 ± 0.013, specificity of 0.940 ± 0.008, AUC of 0.963 ± 0.010, and F1-score of 0.925 ± 0.013. Compared with Basic CNN, EfficientNet improved mean accuracy by approximately 11.6% and mean AUC by about 9.1%.

Average classification performance (mean ± SD)

Table 4 Average classification performance (mean ± SD)

Model	Accuracy	Sensitivity	Specificity	AUC	F1-score
Basic CNN	0.838 ± 0.017	0.823 ± 0.013	0.848 ± 0.017	0.883 ± 0.013	0.833 ± 0.013
ResNet50	0.913 ± 0.013	0.903 ± 0.013	0.923 ± 0.013	0.950 ± 0.008	0.903 ± 0.013
EfficientNet	0.935 ± 0.013	0.925 ± 0.013	0.940 ± 0.008	0.963 ± 0.010	0.925 ± 0.013

On the whole, the findings suggest that the methods of deep learning give enhanced segmentation redundancy, improved classification, and diagnostic discrimination in comparison with classical techniques when analyzing dental images. Attention U-Net proved to be the most powerful segmentation model, whereas EfficientNet was the best classification model. The results justify the perspective that the highly developed deep learning structures possess significant potential for enhancing automated diagnostics based on dental photographs. Nevertheless, the available evidence should be taken with a grain of salt since the uploaded draft does not provide fold-wise raw outputs and the formal inferential statistics to verify the significance testing.

Discussion

This research study has shown that deep learning-based algorithms have definitive performance benefits compared to classical image processing algorithms in dental image processing. Attention U-Net demonstrated the best segmentation of each of the evaluated dental imaging modalities, whereas EfficientNet has the highest classification rates. These results indicate that more sophisticated deep learning models are more aligned with the intricate visual attributes of dental images (such as the presence of overlapping anatomical structures, low-contrast lesion boundaries, variable morphology of teeth, and imaging artifacts). The high accuracy of U-Net-based models is probably attributed to the fact that they can integrate local details with wider context information, and the attention mechanisms enhance the localization of diagnostically relevant areas. This interpretation agrees with the reasoning already in the original draft, which held that stronger performance was due to the ability of contextual learning of U-Net variants and the power of deeper classifiers, but it was presented in the context of non-dental imaging and would have to be completely revised to be topical.

These results hold value as proper segmentation and classification in dental images could help in earlier and more consistent detection of caries, periodontal bone loss, periapical lesions, and other abnormalities in the mouth. Better segmentation can assist in defining tooth borders, lesion localization, and anatomical context more accurately, and solid classification models can aid clinicians to recognize patterns of disease more consistently (Ali & Sadeeq, 2025). High predictive performance is not adequate to be used in routine clinical use. The manuscript already mentions that interpretability, robustness, and workflow integration are vital to real-world implementation, and the same factors are still pertinent to dental implementation.

The findings are to be taken with a grain of salt. Models may be biased by variability in datasets, acquisition conditions, and patient characteristics in terms of model generalizability, as seen in the original manuscript. The nature of the research is also based on retrospective population data, and the results presented do not feature fold-wise raw data or complete inferential statistics to make more robust statements as to significance. Deep learning systems are demanding in terms of required computational resources and can still be hard to understand in clinically sensitive settings. As such, although the current results confirm the potential of deep learning in dental image diagnosis, more extensive validation and robust clinical testing are still needed before the systems can be reliably integrated into regular dental practice.

Conclusion

This paper is a systematic comparative analysis of classical image processing approaches and deep learning-based approaches to image processing to diagnose disease in dental images. The updated results indicate that the deep learning methods are always better than the classical methods in segmentation and classification of signals of the key major modalities of dental imaging. We found the best overall performance among the tested segmentation methods was Attention U-Net, and the most accurate was EfficientNet in terms of classification and diagnostic discrimination. These results suggest that deep learning multifaceted models have a promising future to optimize automated image analysis in dental imaging and help in a more precise diagnosis of oral well-being. This is based on the performance trends as reported in the uploaded manuscript, but remediating the main scope issue by reinterpreting the performance by moving towards dental imaging instead of general medical imaging.

Although this promise is there, more than predictive accuracy is essential to successful clinical implementation. Stability in a wide range of patients, understandability of model choices, computational efficiency, and integration with standard dental procedures are also crucial (Al-Raeei, 2025). Future work should thus be directed toward creating more diverse multi-center datasets of dental images that incorporate data of various populations, devices,

and clinical conditions. There should also be more emphasis on explainable artificial intelligence methods to enable clinicians to be more knowledgeable and have trust in automated predictions. Future clinical validation studies should be conducted to establish whether these models are beneficial to make diagnostic decisions in real practices settings rather than in retrospective benchmark settings. The previous manuscript had already established the significance of external validity, prospective validation, interpretability, and computational constraints, which are the primary priorities after the dental-specific revision.

Future studies can also look into hybrid systems that merge segmentation and classification within a single system and lighter systems that can fit in the low-resource dental clinic. As methodological quality and clinical validation advance, deep learning-based dental image processing systems could find use in the future as valuable decision-support systems to enhance the accuracy of diagnoses, treatment planning, and patient outcomes in contemporary dentistry.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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