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Genset Radiology: Deep Learning Approaches for Periapical Lesion Detection on IOPA

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ABSTRACT-

Artificial intelligence (AI) has transformed diagnostic radiology by introducing automation, precision, and reproducibility. Intraoral periapical (IOPA) radiographs remain indispensable for detecting periapical lesions, yet interpretation accuracy is often limited by observer subjectivity and image quality. AI-driven algorithms, especially deep learning architectures, have demonstrated significant promise in identifying and classifying periapical pathologies. This narrative review synthesizes evidence from recent literature on the applications of AI in the detection and diagnosis of periapical lesions using IOPA radiographs. Studies indicate that convolutional neural networks (CNNs) achieve diagnostic performance comparable to trained radiologists, improving early detection and reducing diagnostic errors. The review discusses various AI models, their clinical relevance, limitations, and future implications for oral medicine and radiology. Despite advancements, challenges related to data diversity, algorithm transparency, and ethical compliance persist. The integration of AI into dental diagnostics marks a paradigm shift toward precision imaging and augmented decision-making in oral healthcare.

Keywords: Artificial intelligence; Deep learning; Intraoral periapical radiographs; Periapical lesions; Diagnostic imaging; Oral radiology.

INTRODUCTION

Periapical lesions are among the most prevalent findings in dental practice and are significant for endodontic diagnosis, treatment planning, and prognosis. These lesions often start from pulpal infection, trauma, or chronic inflammation and can lead to bone deterioration, root resorption, or even systemic impact if ignored [1]. Clinical knowledge and personal expertise are routinely utilized to interpret intraoral periapical radiographs (IOPA), which can result in variability and sometimes missed detection, especially in early-stage or moderate diseases [2]. To maximize endodontic treatments and stop disease growth, early and correct detection is key. Artificial intelligence (AI), particularly deep learning models such as convolutional neural networks (CNNs), allows automatic, objective, and reproducible analysis of diagnostic imaging [3]. CNNs are able to identify barely noticeable changes in periapical radiolucency, lamina dura integrity, and the density of bones that may be awkward for human gaze to perceive [4]. AI models also enable quantitative assessment of lesion size, track healing over time, and forecast probable treatment outcomes, increasing decision-making in endodontics [5]. Additionally, AI is a useful teaching tool that helps dentistry students recognize radiographic aspects more accurately by giving them feedback [6]. Integration of AI into everyday clinical practice improves diagnostic confidence, lowers human error, and allows evidence-based treatment planning [7]. Large-scale epidemiological studies, population screening initiatives, and lesion prevalence investigations can all benefit using AI [8,9]. Combining clinical experience with AI-driven insights can lead to increased diagnostic accuracy, improved treatment planning, and better patient outcomes [10]. This narrative review discusses the principles, applications, advantages, limitations, preprocessing techniques, segmentation approaches, educational use, and future scope of AI in diagnosing periapical pathology using IOPA radiographs, supported by contemporary literature.

PERIAPICAL LESIONS AND DIAGNOSTIC CHALLENGES:

IOPA radiographs are frequently utilized because to their high resolution, low cost, minimum radiation exposure, and ability to provide precise pictures of periapical tissues, lamina dura, and the ligament that surrounds the periodontal area [3]. However, there are restrictions. Two-dimensional imaging cannot adequately depict three-dimensional structures, and superimposition of nearby anatomical characteristics could conceal lesions, particularly in posterior teeth or locations with complicated root architecture [4]. Restorations, metal posts, and anatomical differences can further impair interpretability [5]. Inter- and intra-observer heterogeneity in diagnosing apical periodontitis has been well-documented, with clinician experience, weariness, and subjective interpretation contributing to variations [6]. By offering objective and repeatable lesion detection, identifying problem areas, and lowering diagnostic mistakes, AI systems support radiographic interpretation [7]. AI also enables rapid analysis of large datasets, suitable for high-volume practices, population-level screening, and epidemiological studies [8,9]. AI-guided feedback enhances students' diagnostic abilities and helps them identify minor radiographic characteristics in educational contexts [10]. AI can also monitor lesion healing or progression following endodontic treatment, which helps doctors in patient management and follow-up planning [11].

Table 1. Advantages and limitations of IOPA radiographs

Feature	Advantage	Limitation	Additional Note
Resolution	High for localized areas	Limited FOV for large lesions	Detects subtle radiolucencies but cannot visualize full jaw anatomy [3]
Radiation dose	Low	Cannot detect 3D structures	Safe for repeated imaging, including pediatric patients [3]
Cost	Low	Overlapping anatomy may obscure lesions	Affordable for routine screening and research [4]
Availability	Widely available	Interpretation depends on clinician experience	Accessible in most clinics; image quality depends on operator skill [5]

FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE IN DENTAL IMAGING

MACHINE LEARNING

Machine learning (ML) techniques rely on manually extracted features such as pixel intensity, texture, and edge gradients to identify images [6]. Classical ML models—including support vector machines, random forests, and artificial neural networks—have been applied to periapical lesion identification [6]. Large annotated datasets and meticulous feature engineering are necessary for these techniques, which may restrict their scalability and generalizability [7]. When applied to complex radiographic data, machine learning (ML) typically performs worse than deep learning models, while it can identify subtle patterns that are difficult for humans to see [8].

DEEP LEARNING

Subtle differences in bone density, lesion shape, and texture can be detected thanks to deep learning (DL), especially CNNs, which automatically learn hierarchical features from picture data [7, 8]. CNN designs such as ResNet, DenseNet, VGGNet, and U-Net are extensively utilized for classification and segmentation tasks in dental imaging [8,9]. DL lowers the requirement for manual feature extraction, allowing scalable application over huge datasets. Transfer learning enables pre-trained models to adapt to smaller dental datasets, enhancing performance with minimum retraining [9,10]. Additionally, explainable AI (XAI) methods improve interpretability and clinician trust by visualizing regions that contribute to predictions [10].

AI ALGORITHMS IN PERIAPICAL DIAGNOSIS:

AUTOMATED DETECTION

CNNs can detect periapical lesions with high sensitivity, often outperforming general dentists in diagnosing modest or early-stage radiolucencies [11]. Clinicians can concentrate on complicated patients thanks to automated detection, which also makes sure that little lesions are not missed. AI systems can process many pictures rapidly, enabling high-throughput analysis in clinical or research situations [12]. By creating probability maps, CNNs highlight suspicious regions, supporting faster and more accurate diagnoses. Furthermore, automated identification permits longitudinal tracking of lesion progression and healing post-treatment, which is critical for evaluating endodontic therapy outcomes [13].

Level of Lesion Intensity

AI can classify lesion severity using characteristics such as size, boundary definition, and radiodensity [14]. Grading lesion severity supports clinicians in deciding between conservative endodontic therapy or surgical intervention. Certain AI models improve interpretability and improve patient communication by producing color-coded outputs that signal severity. This feature also permits monitoring of illness progression in follow-ups or research projects, offering quantitative comparisons [15].

Variation Between Lesion Types

Advanced AI models can identify granulomas, radicular cysts, and scar tissue based on radiographic texture and density patterns [12,13]. Although histology remains the gold standard, AI provides crucial preoperative information for clinical decision-making. Differentiation aids in planning apical procedures, forecasting healing potential, and identifying the need for additional diagnostic tests.

Lesion Segmentation and Labelling

Lesion boundaries are accurately defined by segmentation models like U-Net and Mask R-CNN [11]. Quantitative measurement of area and volume permits monitoring of healing over time, comparison between patient visits, and objective assessment of treatment effects [14]. Segmented photos can also serve as annotated datasets for training future AI models, enhancing accuracy and resilience.

Reducing Observer Bias

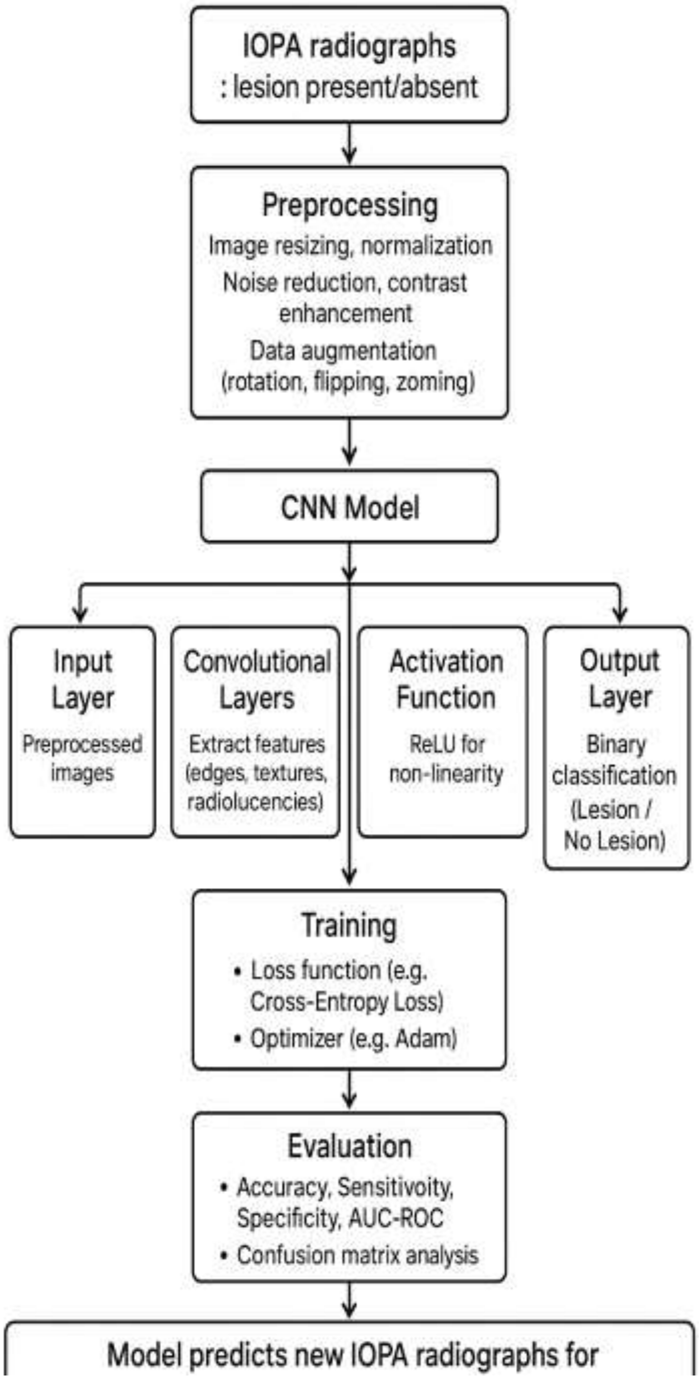
AI decreases inter- and intra-observer variances, ensuring standardized interpretation across doctors and students [14]. By identifying small radiographic changes, AI decreases missed diagnoses and enhances training efficiency. In multicenter trials, AI ensures consistent evaluation across heterogeneous datasets and operators, boosting research reliability [15].

FLOWCHART OF A CNN MODEL APPLIED TO IOPA RADIOGRAPHS FOR PERIAPICAL LESION DETECTION

Steps include:

- Image acquisition from IOPA radiographs
- Preprocessing: noise reduction, normalization, augmentation
- Feature extraction through convolution layers
- Pooling and dimensionality reduction
- Fully connected layers for classification
- Output: lesion probability map and optional segmentation mask
- Visualization of highlighted regions to aid interpretability

Figure1. Schematic of a periapical lesion on an IOPA radiograph.



PRELIMINARY PROCESS AND DATA AUGMENTATION

To enhance AI performance, data preprocessing and augmentation are crucial:

- Noise Reduction: Median or Gaussian filtering reduces random artifacts while preserving lesion edges [17].
- Contrast Enhancement: Adaptive histogram equalization improves visibility of modest radiolucencies [18].
- Normalization: Standardizes intensity ranges across radiographs from different machines, improving generalizability [19]
- Augmentation: Rotations, flips, scaling, and synthetic noise prevent overfitting and increase robustness [20].
- Edge Enhancement: Improves visualization of cortical bone and periodontal ligament space [17].
- Dataset Balancing: Ensures underrepresented lesion types are adequately trained [19].

- Preprocessing ensures AI models are robust across diverse clinical settings, reduces bias from different imaging systems, and improves reproducibility of results [20].

AI AND CLINICIANS' COMPARATIVE PERFORMANCE

According to studies, CNN models can detect apical periodontitis with 90–93% accuracy, which is on par with or superior to general dentists [15,16]. AI maintains consistent sensitivity and specificity throughout vast datasets, but human performance may vary due to fatigue, experience, or complex anatomy. Comparative studies indicate that AI is particularly efficient in recognizing early-stage lesions and modest radiolucencies [15]. Heatmaps and probability overlays given by AI assist doctors in analyzing uncertain areas, enhancing diagnostic confidence [16]. Combining AI with physician knowledge frequently delivers superior outcomes compared to either alone. The integration of AI into clinical operations significantly accelerates report generation, enabling efficient patient care in high-volume practices [16].

Metric	CNN Model	General Dentist	Specialist	Additional Note
Accuracy	92%	81%	94%	Stable performance across dataset variations [15]
Sensitivity	0.91	0.78	0.92	AI better detects early-stage lesions [15]
Specificity	0.93	0.83	0.95	Comparable across all evaluators [16]
F1-score	0.90	0.79	0.93	Reflects balance of precision and recall [15]
AUC	0.95	0.85	0.96	Demonstrates strong discrimination [16]

Table 2. Comparison of AI vs clinician performance metrics

CLINICAL APPLICATIONS

Applications of AI include:

- Identifying overlapping anatomical regions and concealed lesions in molars [10,11].
- Monitoring post-endodontic healing throughout time [13]
- Encouraging extensive epidemiological research [18]
- Aiding minimally invasive endodontics by recognizing early pathology [14]
- Preoperative evaluation for retreatment or apical surgery [12]
- Automated reporting for tele-dentistry and multicenter collaboration [15]
- AI-assisted interpretation enhances decision-making in difficult cases, supports precision dentistry, and lowers diagnostic delays [15,16].
- Visual overlays help clinicians convey illness state and therapy rationale to patients [17].

INTEGRATION WITH OTHER IMAGING MODALITIES

Hybrid AI models combining IOPA radiographs with CBCT datasets can improve diagnostic accuracy in complex anatomical regions [25]. For more accurate lesion localization, volumetric evaluation, and treatment planning, multimodal AI makes use of complementary 2D and 3D imaging data. Co-registration of 2D and 3D images enables clinicians to visualize lesion area, proximity to key structures, and bone density changes. Integration with demographic and clinical data may further boost predictive accuracy and tailored therapy recommendations [25].

BENEFITS AND ADVANTAGES

When it comes to the identification and diagnosis of periapical lesions using IOPA radiographs, AI has many benefits. One of the primary benefits is enhanced diagnostic accuracy, as deep learning models such as CNNs can detect subtle lesions and radiolucencies that might be overlooked by clinicians, particularly in early-stage pathology [17]. AI systems are also highly efficient, capable of analyzing large numbers of radiographs rapidly, which reduces clinician workload and accelerates patient management [18]. In educational settings, AI serves as a standardized teaching tool, providing objective feedback to students and helping them recognize minor radiographic changes with greater confidence [19]. Quantitative monitoring, where AI can quantify lesion size and evaluate changes over time, is another important benefit. This allows doctors to track healing and estimate the effectiveness of endodontic treatment [24]. Furthermore, AI may be integrated into digital radiography software, enabling real-time decision support, identifying worrisome areas, and supporting physicians in treatment planning [20]. AI also lowers observer variability, ensuring uniform interpretation across different doctors and training situations [14]. Beyond clinical contexts, AI provides population-level screening and epidemiological investigations, enabling the measurement of lesion prevalence and treatment effects on a greater scale [18]. Collectively, these advantages contribute to enhanced patient care, increased workflow efficiency, and more informed clinical decision-making.

LIMITATIONS

Despite its obvious advantages, AI has several limitations and obstacles in clinical deployment. The quality and correctness of datasets used for training AI models strongly influence their performance, and poorly annotated data might lead to inaccurate predictions or missing lesions [21]. AI models may also have low generalizability, especially if trained on a single population, making them less accurate when applied to varied patient groups [22]. Since IOPA radiographs are two-dimensional, overlapping anatomical features can obscure lesions, reducing AI's ability to detect certain disorders [23]. Additionally, the interpretability of deep learning models remains an issue, as physicians may not completely understand the rationale behind AI predictions, thereby impacting trust in automated findings [24]. Ethical and regulatory constraints further complicate clinical deployment, including questions of liability in case of misdiagnosis and the requirement for validation before widespread usage [24]. Variations in imaging instruments, exposure settings, and patient placement can potentially impair AI performance, underscoring the significance of thorough preprocessing and standardization [21]. Finally, integrating AI into everyday procedures needs investment in infrastructure, software, and training, which may not be possible in all healthcare contexts [20]. These constraints underline the need for meticulous validation, continual model refinement, and integrated clinician-AI decision-making to ensure safe and successful use.

FUTURE ASPECTS

Emerging directions include:

- Federated learning for secure AI training across institutions [25]
- Explainable AI providing interpretable outputs for clinicians [24]
- Real-time chairside detection during routine imaging [20]
- Global AI-assisted screening programs for underserved populations [18,25]
- Hybrid models combining CNNs with rule-based algorithms for complex diagnostics [25]
- Predictive modelling of lesion progression and treatment response [24]
- Integration with augmented reality for enhanced visualization [17]
- Continuous learning models adapting to new datasets and imaging modalities [25].
- Integration with three-dimensional modalities such as cone-beam computed tomography (CBCT) and incorporation of federated learning could further improve performance while preserving data security [26].

CONCLUSION

Artificial intelligence has demonstrated remarkable capability in detecting and delineating periapical lesions on intraoral periapical radiographs. Deep-learning algorithms, particularly convolutional networks, provide objective and reproducible assessments that complement the clinician's expertise. Although challenges in data diversity, validation, and ethical regulation remain, AI is poised to become an indispensable diagnostic adjunct in oral radiology and endodontics. Continued collaboration between dental specialists, computer scientists, and regulatory bodies will ensure safe and effective translation of AI into daily practice.

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