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From Pixels to Precision: A Comprehensive Review of Artificial Neural Networks and Convolutional Neural Networks in Contemporary Endodontics

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Abstract: ***The integration of Artificial Intelligence (AI) into dentistry has significantly transformed diagnostic and therapeutic approaches, particularly in endodontics. Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), key subsets of machine learning and deep learning, respectively, have demonstrated remarkable potential in analysing complex clinical and radiographic data. This review critically evaluates current literature on ANN and CNN applications in endodontics, focusing on diagnostic accuracy, treatment planning, outcome prediction, and clinical workflow enhancement. CNN-based models have shown superior performance in interpreting periapical radiographs and cone-beam computed tomography (CBCT) scans, enabling early detection of periapical pathologies, root fractures, and anatomical variations. ANN models, on the other hand, have been widely used for predictive analytics and decision support systems. Despite promising outcomes, challenges such as dataset heterogeneity, lack of external validation, ethical concerns, and limited clinical integration persist. Future advancements in explainable AI and real-time clinical applications are expected to bridge the gap between research and practice. This review highlights the transformative potential of ANN and CNN while emphasizing the need for standardized protocols and robust clinical validation.***

Keywords: Artificial Intelligence, Artificial Neural Network, Convolutional Neural Network, Deep Learning, Endodontics, CBCT, Periapical Lesions

1. Introduction

Endodontics is a highly specialized field of dentistry that depends on precise diagnosis and meticulous treatment planning to ensure long-term success. Conventional diagnostic approaches, including clinical examination and radiographic interpretation, are often limited by subjectivity, operator experience, and the inherent constraints of two-dimensional imaging. These limitations can lead to variability in diagnosis and may affect treatment outcomes. In recent years, Artificial Intelligence (AI) has emerged as a transformative tool in healthcare, offering the ability to analyze complex datasets with high accuracy and consistency. Within AI, Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) have gained particular attention in endodontics. ANN models are effective in handling structured clinical data and predicting treatment outcomes, while CNN models excel in analysing radiographic images such as periapical radiographs and cone-beam computed tomography scans.

The integration of these technologies into endodontics has opened new possibilities for improving diagnostic precision, identifying anatomical complexities, and supporting evidence-based decision-making. However, despite rapid advancements, challenges related to validation, standardization, and clinical implementation remain. This review aims to provide a comprehensive overview of the role of ANN and CNN in endodontics, focusing on their fundamental principles, clinical applications, comparative performance, and future potential in enhancing patient care.

2. Methodology

A structured literature search was conducted across electronic databases including PubMed, Scopus, Web of Science, and Google Scholar for articles published between 2015 and 2025. Keywords used included *“Artificial Neural Network,” “Convolutional Neural Network,” “Deep Learning,” “Endodontics,” “CBCT,” and “Periapical Lesions.”*

Inclusion criteria:
- Original research, systematic reviews, and meta-analyses
- Studies focusing on ANN/CNN applications in endodontics
- English-language publications

Exclusion criteria:
- Non-dental AI studies
- Case reports with limited generalizability
- Studies lacking methodological clarity

3. Fundamentals of AI in Endodontics

The application of Artificial Intelligence (AI) in endodontics is grounded in computational models that simulate human cognition, learning, and pattern recognition. At its core, AI enables machines to learn from data, identify patterns, and make decisions with minimal human intervention. In endodontics- where diagnosis and treatment planning heavily rely on interpretation of radiographic and clinical data- AI provides a powerful adjunct to overcome subjectivity and variability.

AI in this domain primarily operates through Machine Learning (ML) and its advanced subset, Deep Learning (DL). While ML algorithms rely on structured data and predefined features, DL models- particularly Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN)- are capable of automatically extracting complex features from large datasets, especially images such as periapical radiographs and CBCT scans.

3.1 Artificial Neural Networks (ANN)

Artificial Neural Networks are computational frameworks inspired by the structure and function of biological neural systems. They consist of interconnected processing units called neurons, organized into three primary layers: input, hidden, and output layers. Each connection between neurons is assigned a weight, which is iteratively adjusted during the training process to minimize prediction error. The fundamental strength of ANN lies in its ability to model nonlinear relationships between multiple variables- an essential feature in endodontics, where treatment outcomes are influenced by a complex interplay of biological, anatomical, and procedural factors.

In endodontic applications, ANN models are typically trained using clinical datasets that include parameters such as patient demographics, pulp status, lesion size, root canal morphology, and procedural variables. Through supervised learning, the model learns to associate input variables with specific outcomes, such as treatment success or failure. A key advantage of ANN is its versatility in handling structured clinical data and generating predictive outputs. For example, ANN-based systems have been employed to:
- Predict the prognosis of root canal treatments
- Assist in decision-making for retreatment versus extraction
- Classify pulpal and periapical conditions based on clinical indicators

However, ANN models are highly dependent on the quality and completeness of input data. Missing or biased data can significantly affect model performance. Additionally, traditional ANN architectures are less efficient in processing image data compared to CNNs, as they lack inherent mechanisms for spatial feature extraction.

3.2 Convolutional Neural Networks (CNN)

Convolutional Neural Networks represent a specialized class of deep learning models designed specifically for image analysis. Unlike traditional ANN, CNNs are capable of automatically learning spatial hierarchies of features from raw image data, making them highly suitable for radiographic interpretation in endodontics.

A typical CNN architecture consists of multiple layers:
- Convolutional Layers: These layers apply filters (kernels) to the input image to detect features such as edges, textures, and shapes.
- Activation Functions: Introduce nonlinearity, enabling the model to learn complex patterns.
- Pooling Layers: Reduce dimensionality while preserving important features, improving computational efficiency.
- Fully Connected Layers: Perform classification based on the extracted features.

One of the most significant advantages of CNNs is their ability to perform automatic feature extraction, eliminating the need for manual input or feature engineering. This is particularly valuable in endodontics, where subtle radiographic changes—such as early periapical radiolucencies or fine fracture lines- may be difficult for clinicians to detect.

CNNs have been extensively applied in:
- Detection of periapical lesions on radiographs and CBCT
- Identification of root canal morphology and additional canals
- Diagnosis of vertical root fractures
- Segmentation of anatomical structures in 3D imaging

Their performance is often evaluated using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC), with many studies reporting high diagnostic reliability.

3.3 Deep Learning Workflow in Endodontics

The implementation of AI models in endodontics typically follows a structured workflow:
- Data Acquisition: Collection of radiographic images (periapical, CBCT) and clinical data
- Data Annotation: Labelling of images (e.g., presence of lesion, canal morphology)
- Preprocessing: Image normalization, noise reduction, and augmentation to improve model robustness
- Model Training: Feeding annotated data into ANN or CNN models
- Validation and Testing: Evaluation of model performance on unseen datasets
- Deployment: Integration into clinical or research settings

Each step is critical, as errors in annotation or preprocessing can significantly impact model accuracy.

3.4 Learning Paradigms Relevant to Endodontics

AI models in endodontics primarily utilize supervised learning, where labelled datasets guide the training process. However, emerging approaches include:
- Unsupervised Learning: Identifies hidden patterns in unlabelled data (e.g., clustering anatomical variations)
- Semi-supervised Learning: Combines labelled and unlabelled data to improve efficiency
- Reinforcement Learning: Though less common, it has potential in optimizing treatment strategies

These paradigms offer opportunities to overcome the limitation of limited annotated datasets, which is a major challenge in dental AI research.

3.5 Key Technical Considerations

Several technical factors influence the performance of AI models in endodontics:
- Dataset Size and Diversity: Larger and more diverse datasets improve generalizability
- Annotation Quality: Expert-labelled data is essential for accurate training
- Overfitting: Models may perform well on training data but poorly on new data
- Computational Resources: Deep learning models require high processing power
- Model Interpretability: Clinically relevant explanations are necessary for acceptance

3.6 Clinical Relevance of AI Fundamentals

Understanding the foundational principles of ANN and CNN is crucial for clinicians to critically evaluate AI-based tools. Rather than functioning as standalone diagnostic systems, these technologies are best viewed as augmentative tools that enhance clinical judgment.

For instance, a CNN-based system identifying a periapical lesion should be interpreted alongside clinical findings, pulp vitality tests, and patient history. Similarly, ANN-based predictions should be used to support- not replace- clinical decision-making.

4. Clinical Applications of Artificial Neural Networks and Convolutional Neural Networks in Endodontics

The application of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) in endodontics has significantly evolved over the past decade, primarily driven by advancements in digital imaging and computational power. These technologies are increasingly being explored to enhance diagnostic precision, improve treatment outcomes, and streamline clinical workflows. The following sections provide a detailed and critical analysis of their major clinical applications.

4.1 Detection of Periapical Pathologies

Accurate diagnosis of periapical lesions is fundamental to endodontic treatment planning. Conventional radiographic interpretation is often limited by two-dimensional imaging, anatomical superimposition, and interobserver variability. CNN-based models have demonstrated high diagnostic performance in detecting periapical radiolucencies on both periapical radiographs and cone-beam computed tomography (CBCT) images. These models are trained on large annotated datasets and are capable of identifying subtle changes in bone density that may not be visible to the human eye, particularly in early-stage lesions. Studies have reported that CNN systems can achieve sensitivity and specificity comparable to, or in some cases exceeding, those of experienced endodontists under controlled conditions. Furthermore, three-dimensional analysis using CBCT enhances lesion detection by eliminating superimposition and providing volumetric assessment. However, despite promising results, variability in image quality, differences in imaging protocols, and lack of standardized datasets may influence model performance. Therefore, clinical validation across diverse populations remains essential.

4.2 Root Canal Morphology Identification

The complexity and variability of root canal systems represent a major challenge in endodontics. Missed canals, such as the second mesiobuccal canal (MB2) in maxillary molars, are a common cause of treatment failure. CNN-based models have shown considerable potential in identifying root canal configurations using radiographic and CBCT data. By analysing spatial patterns and anatomical landmarks, CNNs can detect additional canals and variations in root morphology with a high degree of accuracy. These systems can serve as a valuable adjunct during preoperative assessment, enabling clinicians to anticipate anatomical complexities and modify access cavity design accordingly.

4.3 Diagnosis of Vertical Root Fractures

Vertical root fractures are among the most challenging conditions to diagnose in endodontics due to their often subtle and nonspecific radiographic appearance. Conventional diagnostic methods frequently rely on indirect signs, leading to delayed or inaccurate diagnosis.

CNN algorithms have demonstrated promising capabilities in detecting vertical root fractures, particularly when trained on CBCT datasets. These models can identify fine fracture lines and associated radiographic patterns that may be overlooked during manual interpretation. The use of AI in this context has the potential to reduce false-negative diagnoses and improve treatment planning.

However, it is important to note that artifacts in CBCT imaging, such as beam hardening and noise, can affect model performance. Additionally, the presence of metallic restorations may further complicate image interpretation.

4.4 Working Length Determination

Accurate determination of working length is critical for effective root canal therapy. Traditional methods include radiographic assessment and electronic apex locators, both of which are subject to operator variability and technical limitations.

ANN-based systems have been investigated as tools for estimating working length by analyzing radiographic data and integrating clinical parameters. These models aim to provide objective and reproducible measurements, thereby reducing reliance on subjective interpretation.

While preliminary studies suggest that ANN models can achieve acceptable levels of accuracy, their clinical application remains limited. Integration with real-time imaging systems and electronic apex locators may enhance their utility in future practice.

4.5 Outcome Prediction and Prognostic Assessment

One of the most valuable applications of ANN in endodontics is its ability to predict treatment outcomes based on multiple input variables. These models can incorporate patient-related factors, preoperative conditions, and procedural details to estimate the likelihood of treatment success or failure. Such predictive systems can assist clinicians in decision-making, particularly in complex cases where the choice between retreatment, surgical intervention, or extraction is not straightforward. By providing a probabilistic assessment, ANN models support evidence-based treatment planning and patient communication. Despite their potential, these models are highly dependent on the quality and completeness of input data. Incomplete datasets or biased training samples may compromise predictive accuracy. Moreover, the lack of transparency in decision-making processes may limit clinician trust.

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4.6 Automated Image Segmentation and Anatomical Mapping

CNN-based models have also been applied to the segmentation of dental structures in radiographic and CBCT images. This includes the identification and delineation of root canals, periapical lesions, and surrounding anatomical structures. Automated segmentation facilitates quantitative analysis, such as lesion volume measurement and canal curvature assessment, which can aid in treatment planning and outcome evaluation. It also reduces the time required for manual annotation and improves consistency across cases. However, segmentation accuracy can be affected by image artifacts, anatomical variations, and limitations in training data. Continuous refinement of algorithms and incorporation of larger datasets are necessary to improve reliability.

4.7 Detection of Resorptive Defects

External and internal root resorption are often difficult to diagnose in their early stages. CNN models trained on CBCT images have shown potential in detecting resorptive defects with high accuracy. Early identification allows for timely intervention, which is critical for preserving tooth structure and function. As with other applications, the success of these models depends on the availability of high-quality annotated datasets and validation in clinical settings.

5. Performance Comparison Between Artificial Neural Networks and Convolutional Neural Networks in Endodontics

The comparative performance of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) in endodontics reflects their fundamentally different architectures, data-processing capabilities, and clinical applications. While both models belong to the broader domain of machine learning, their effectiveness varies depending on the nature of the task—particularly whether the problem involves structured clinical data or image-based diagnostics.

5.1 Architectural Differences and Their Clinical Implications

ANN models are composed of fully connected layers in which each neuron processes input data in a generalized manner. This structure allows ANN to effectively model complex, nonlinear relationships between multiple variables. However, ANN lacks inherent mechanisms for spatial feature recognition, making it less suitable for direct image analysis without prior feature extraction.

In contrast, CNN models are specifically designed to process image data through convolutional operations that preserve spatial hierarchies. By applying multiple filters across an image, CNNs can automatically learn features such as edges, contours, and textures, which are essential for interpreting radiographic images. This architectural advantage makes CNN the preferred model for tasks involving periapical radiographs and CBCT scans. Clinically, this distinction translates into CNN outperforming ANN in diagnostic imaging tasks, whereas ANN remains valuable for predictive modeling and decision support.

5.2 Diagnostic Accuracy in Image-Based Applications

A consistent finding across the literature is the superior performance of CNNs in radiographic interpretation. CNN-based models have demonstrated high sensitivity and specificity in detecting periapical lesions, identifying root canal morphology, and diagnosing vertical root fractures. The ability of CNNs to process raw image data without manual feature engineering significantly enhances their diagnostic accuracy. Additionally, CNNs benefit from data augmentation techniques, which improve robustness and reduce overfitting. ANN models, on the other hand, are not inherently designed for image processing and typically require pre-processed or manually extracted features. As a result, their performance in image-based tasks is generally inferior to that of CNNs.

5.3 Predictive Modeling and Decision Support

In the domain of predictive analytics, ANN models demonstrate a distinct advantage. Their ability to integrate multiple clinical variables- such as patient demographics, lesion characteristics, and procedural factors- enables them to generate reliable predictions regarding treatment outcomes.

ANN-based systems have been successfully used to:
- Predict the success or failure of root canal treatments
- Assist in retreatment decision-making
- Evaluate risk factors associated with endodontic failure

CNNs, while capable of classification tasks, are less effective in handling structured, non-image data unless combined with other architectures. Therefore, ANN remains the preferred model for clinical decision support systems.

5.4 Data Requirements and Computational Complexity

CNN models generally require large, high-quality datasets for training, particularly annotated imaging datasets. The process of labelling radiographic images is time-consuming and requires expert input, which can limit dataset availability. Furthermore, CNNs demand significant computational resources, including high-performance graphics processing units, for efficient training. ANN models, although still data-dependent, can perform adequately with smaller datasets, especially when dealing with structured clinical variables. They are also less computationally intensive compared to CNNs, making them more accessible in resource-limited settings. However, both models are susceptible to overfitting when trained on limited or non-representative datasets, emphasizing the importance of dataset diversity and proper validation.

5.5 Generalizability and Robustness

Generalizability refers to the ability of a model to perform well on unseen data. CNN models trained on homogeneous datasets may exhibit reduced performance when applied to images acquired using different imaging systems or protocols. Variability in CBCT machines, resolution, and exposure settings can affect model robustness. Similarly, ANN models may suffer from reduced generalizability if trained on datasets that do not adequately represent diverse patient populations. The inclusion of multicentre data and external validation is essential for improving the reliability of both models.

5.6 Interpretability and Clinical Acceptance

One of the major challenges associated with both ANN and CNN models is their limited interpretability. These models are often described as "black-box" systems, as they do not provide clear explanations for their predictions. CNN models have made some progress in this area through visualization techniques such as heat maps, which highlight regions of interest in an image. These tools can improve clinician understanding and trust to some extent. ANN models, however, offer limited interpretability, particularly when dealing with complex, multilayered architectures. The lack of transparency in both systems remains a significant barrier to clinical adoption, as clinicians require clear and explainable outputs to make informed decisions.

5.7 Integration into Clinical Workflow

From a practical perspective, CNN models are more readily integrated into imaging software and diagnostic platforms, allowing real-time analysis of radiographs and CBCT scans. This makes them highly suitable for chairside applications. ANN models, being primarily used for backend predictive analysis, are less visible in routine clinical workflows but can be incorporated into decision-support systems and digital health records. The ideal clinical system may involve a hybrid approach, combining CNN for image analysis and ANN for predictive modeling, thereby leveraging the strengths of both architectures.

6. Advantages of AI Integration in Endodontics

1) **Improved Diagnostic Accuracy:** CNNs detect subtle radiographic changes, enabling earlier and more precise diagnosis.
2) **Reduced Operator Dependency:** Provides consistent, reproducible results, minimizing variability among clinicians.
3) **Time Efficiency:** Automates data and image analysis, reducing interpretation time.
4) **Enhanced Decision Support:** ANN models analyze multiple variables to guide evidence-based treatment planning.
5) **Personalized Treatment:** Enables patient-specific approaches, improving precision and outcomes

7. Limitations and Challenges

Despite the promising potential of ANN and CNN in endodontics, several limitations hinder their widespread clinical adoption. A primary concern is the **requirement for large, high-quality datasets**, as AI models depend heavily on well-annotated data for accurate training. In many cases, available datasets are limited, heterogeneous, or biased, which can compromise model reliability and generalizability. Another significant challenge is the **lack of external validation and standardization**. Many studies are conducted in controlled environments using single-center data, making it difficult to apply these models universally across different populations and imaging systems.

The **"black-box" nature** of AI models also limits interpretability, reducing clinician trust and acceptance. Additionally, **ethical and legal concerns**, including patient data privacy, informed consent, and liability in case of diagnostic errors, remain unresolved. Finally, **integration into routine clinical workflows** is still limited due to the lack of user-friendly, chairside-compatible systems and the need for clinician training in AI technologies.

8. Future Directions

The future of AI in endodontics is centered on improving clinical applicability and reliability. One important direction is the development of **explainable AI models**, which provide transparent and interpretable outputs, thereby increasing clinician trust and acceptance. There is also a growing need for **large-scale, multicentre prospective studies** to validate AI systems across diverse populations and imaging conditions. Such studies will enhance the generalizability and clinical credibility of these technologies.

Advancements in **real-time AI integration** with imaging systems and dental software are expected to enable chairside decision support, making AI more practical in daily clinical practice. Additionally, **cloud-based platforms and data sharing frameworks** may facilitate continuous model improvement and accessibility. Future innovations may also include **AI-assisted robotic endodontics** and **personalized treatment planning**, where patient-specific data are used to optimize outcomes. Overall, continued interdisciplinary collaboration, standardization, and regulatory development will be essential to fully realize the potential of AI in endodontics.

9. Discussion

The integration of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) into endodontics reflects a broader shift toward precision dentistry, where clinical decisions are increasingly supported by data-driven insights. The findings synthesized in this review highlight that AI-based models, particularly CNNs, have demonstrated substantial potential in enhancing diagnostic accuracy, reducing inter- and intra-observer variability, and improving overall clinical efficiency. However, a deeper examination of the available literature reveals both the strengths and the critical limitations that must be addressed before these technologies can be reliably implemented in routine endodontic practice.

A consistent observation across multiple studies is the superior performance of CNNs in radiographic interpretation, especially in detecting periapical lesions and identifying complex root canal anatomies. This can be attributed to the hierarchical feature extraction capability of CNNs, which allows them to identify subtle radiographic patterns that may not be perceptible to the human eye. In CBCT-based studies, CNNs have shown even higher diagnostic sensitivity due to the availability of three-dimensional data, which reduces anatomical superimposition and enhances lesion detectability.

Nevertheless, it is important to acknowledge that many of these studies are conducted under idealized conditions using curated datasets, which may not accurately reflect the variability encountered in clinical practice, such as differences in image quality, exposure parameters, and patient-specific anatomical variations.

In contrast, ANN models have been predominantly utilized for predictive analytics and decision-support systems. Their ability to process complex, nonlinear relationships between multiple clinical variables makes them particularly useful for outcome prediction and treatment planning. For instance, ANN-based models have been employed to predict the success of root canal treatments by incorporating variables such as patient age, lesion size, microbial status, and procedural factors. While these models offer valuable insights, their clinical utility is often limited by the quality and completeness of input data, as well as the lack of transparency in how predictions are generated.

A critical limitation observed across the literature is the lack of external validation and standardization. Most AI models are trained and tested on datasets derived from single institutions, leading to potential overfitting and reduced generalizability. The absence of multicentre studies and standardized evaluation metrics makes it difficult to compare model performance across different studies. Furthermore, variations in annotation protocols- often dependent on expert opinion—introduce an additional layer of subjectivity, which can influence model training and outcomes.

Another important consideration is the issue of explainability. While CNNs are highly effective in pattern recognition, their "black-box" nature limits the clinician's ability to understand the rationale behind a given diagnosis or prediction. This lack of interpretability can hinder clinical acceptance and raises concerns regarding accountability, particularly in cases of diagnostic errors. Recent developments in explainable AI (XAI), such as heat maps and saliency maps, aim to address this issue by highlighting regions of interest within images; however, these approaches are still in their early stages and require further validation.

Ethical and medico-legal implications also play a significant role in shaping the future of AI in endodontics. The use of patient data for training AI models necessitates strict adherence to data protection regulations and ethical guidelines. Additionally, the question of liability in AI-assisted decision-making remains unresolved—whether responsibility lies with the clinician, the software developer, or both is still a matter of debate. These concerns must be addressed through clear regulatory frameworks before widespread clinical adoption can occur.

From a practical perspective, the integration of AI into daily endodontic workflows presents logistical challenges. Most currently available AI systems are not seamlessly integrated into dental software or imaging platforms, limiting their usability in real-time clinical settings. Moreover, there is a need for adequate training and education of dental professionals to ensure that AI tools are used appropriately and effectively. Without proper understanding, there is a risk of over-reliance on AI outputs, which could potentially compromise clinical judgment.

Despite these challenges, the potential benefits of ANN and CNN in endodontics are substantial. AI has the capacity to serve as a powerful adjunct, enhancing clinician performance rather than replacing it. For example, AI-assisted diagnostic systems can act as a second opinion, improving diagnostic confidence and reducing the likelihood of missed lesions or anatomical variations. In educational settings, AI can also be used as a training tool to help students develop diagnostic skills through interactive feedback.

Future research should focus on addressing the current limitations by conducting large-scale, multicentre, prospective studies that evaluate AI performance in real-world clinical environments. Standardization of datasets, annotation protocols, and evaluation metrics will be essential for ensuring reproducibility and comparability. Additionally, the development of explainable and transparent AI models will be crucial for gaining clinician trust and facilitating regulatory approval.

10. Conclusion

The integration of Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) marks a shift in endodontics toward a data-driven, precision-based approach. CNNs demonstrate high diagnostic accuracy in detecting periapical lesions, root canal morphology, and vertical root fractures, often comparable to human performance, while ANN models show promise in predicting treatment outcomes and supporting clinical decision-making.

However, a gap remains between technological advancements and clinical applicability. Most studies are retrospective, based on limited datasets, and lack external validation, raising concerns about generalizability and reliability. Additionally, the "black-box" nature of deep learning models limits interpretability and clinician trust, highlighting the need for explainable AI systems.
Ethical and regulatory challenges, including data privacy, algorithmic bias, and lack of standardization, must be addressed before routine implementation. AI should be viewed as an adjunct rather than a replacement for clinical expertise.

With further validation, interdisciplinary collaboration, and technological refinement, AI has the potential to significantly enhance diagnostic accuracy, treatment outcomes, and overall patient care in endodontics.

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