RESEARCH ARTICLE

Cognitive Learning Models for Predicting Apical Microleakage Using Pre- and Post-Operative CBCT Data

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ABSTRACT

Apical microleakage remains a major factor affecting the long-term success of endodontic treatment, often leading to treatment failure if undetected. Conventional diagnostic methods rely heavily on clinical expertise and qualitative image interpretation, which can be subjective and limited in sensitivity. This study proposes the application of cognitive learning models to predict apical microleakage by leveraging pre- and post-operative cone-beam computed tomography (CBCT) data. The framework integrates imaging-derived features from both treatment stages to capture structural and morphological changes associated with microleakage development. Advanced learning techniques are employed to model complex spatial patterns and variations within CBCT scans, enabling improved predictive accuracy compared to traditional assessment approaches. Experimental results demonstrate that the proposed cognitive learning-based approach enhances early detection and risk prediction of apical microleakage, supporting more informed clinical decision-making. The findings highlight the potential of intelligent imaging analysis to augment endodontic diagnostics and contribute to improved treatment outcomes.

Keywords: Apical microleakage, Cognitive learning models, Cone-beam computed tomography (CBCT), Endodontics, Medical image analysis, Predictive modeling.

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INTRODUCTION

Apical microleakage remains a critical challenge in endodontic therapy, as it is a major contributing factor to persistent periapical inflammation, delayed healing, and eventual treatment failure. Despite advances in root canal instrumentation, obturation materials, and microsurgical techniques, the inability to reliably detect and predict microleakage at the apical region continues to compromise long-term clinical outcomes. Early and accurate identification of apical sealing deficiencies is therefore essential for improving prognosis and guiding post-operative decision-making.

Cone-beam computed tomography (CBCT) has emerged as a valuable imaging modality in endodontics due to its ability to provide high-resolution, three-dimensional visualization of periapical tissues and root canal anatomy. Unlike conventional radiography, CBCT allows for more precise assessment of periapical lesions, bone healing, and post-surgical outcomes, making it particularly suitable for evaluating subtle structural changes associated with apical microleakage (Allegretti, 2016; Barseghyan, 2016). CBCT has also been increasingly utilized in outcome evaluation following endodontic microsurgery and conservative management of odontogenic pathologies, highlighting its diagnostic versatility and clinical relevance (AKTAŞ et al., 2015; dei Congressi, 2019).

In parallel with imaging advancements, artificial intelligence (AI) and machine learning techniques have gained significant attention in dental research for their capacity to model complex, non-linear relationships within large and heterogeneous datasets. Cognitive learning models, which are inspired by human learning and reasoning processes, offer a promising framework for extracting meaningful patterns from medical imaging data and supporting predictive clinical decision-making. In endodontics, AI-driven approaches have demonstrated potential in image interpretation, diagnosis, and outcome prediction, addressing limitations associated with subjective human assessment and inter-observer variability (Singh, 2022).

The integration of pre- and post-operative CBCT data into cognitive learning models presents a novel opportunity to enhance the prediction of apical microleakage. By learning from temporal changes in anatomical and periapical features, such models can capture subtle indicators of leakage that may not be readily apparent through visual inspection alone. Similar CBCT-based analytical approaches have been successfully applied in evaluating airway volumes and skeletal patterns, underscoring the feasibility of quantitative CBCT analysis in diverse dental and maxillofacial contexts (Duyan & Evlice, 2021).

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Against this backdrop, the application of cognitive learning models for predicting apical microleakage using CBCT data represents a convergence of advanced imaging and intelligent computational methods. This approach has the potential to improve diagnostic accuracy, support evidence-based treatment planning, and ultimately contribute to more predictable endodontic outcomes.

Related Work

Apical microleakage remains a critical factor influencing the long-term success of endodontic treatment, as it is closely associated with persistent periapical inflammation and treatment failure. Conventional assessment methods, including dye penetration, fluid filtration, and radiographic evaluation, have demonstrated limitations in sensitivity, reproducibility, and clinical applicability. With the advancement of imaging and computational techniques, cone-beam computed tomography (CBCT) and artificial intelligence (AI)–based approaches have increasingly been explored to address these shortcomings.

CBCT has become an essential imaging modality in endodontics due to its ability to provide three-dimensional visualization of periapical tissues, root canal morphology, and treatment outcomes. Early academic work demonstrated the superiority of CBCT over two-dimensional radiography in detecting periapical changes and evaluating healing after surgical and non-surgical endodontic procedures. Allegretti emphasized the value of CBCT in outcome evaluation following endodontic microsurgery, particularly in maxillary posterior teeth, highlighting its capacity to detect subtle periapical alterations that may not be visible on conventional radiographs (Allegretti, 2016). Similarly, Barseghyan reported that CBCT-based assessment allows for a more accurate and quantitative evaluation of periapical bone healing, reinforcing its reliability for longitudinal outcome analysis in endodontic research (Barseghyan, 2016).

Beyond outcome assessment, CBCT has been widely applied across dental specialties for structural and volumetric analysis. Studies presented in pediatric and craniofacial research contexts have demonstrated the adaptability of CBCT for evaluating complex anatomical changes, reinforcing its robustness as a diagnostic tool (dei Congressi, 2019). Additional applications, such as airway volume evaluation using CBCT, further illustrate its effectiveness in extracting clinically meaningful spatial features from volumetric datasets, which are essential for computational modeling (Duyan & Evlice, 2021).

The integration of AI and machine learning into dental imaging analysis has expanded rapidly, enabling automated feature extraction, pattern recognition, and predictive modeling. Singh provided a comprehensive overview of AI applications in endodontics, noting that machine learning models have shown promise in tasks such as lesion detection, treatment outcome prediction, and decision support systems (Singh, 2022). Cognitive learning models, in particular, aim to emulate human reasoning by learning from complex, multimodal inputs, making them suitable for interpreting pre- and post-operative CBCT data where spatial and temporal changes are critical.

While AI has been applied to various diagnostic challenges in dentistry, its application to predicting apical microleakage remains limited. Existing studies have primarily focused on qualitative assessments or post-treatment outcome classification rather than predictive modeling using longitudinal imaging data. Case-based and conservative management reports in oral pathology further underscore the importance of accurate imaging interpretation in clinical decision-making, though they often rely on expert judgment rather than automated analysis (AKTAŞ et al., 2015).

Overall, the reviewed literature highlights a convergence of CBCT imaging and AI methodologies in dental research. However, there is a clear research gap in leveraging cognitive learning models to integrate pre- and post-operative CBCT data for the specific prediction of apical microleakage. Addressing this gap offers the potential to enhance diagnostic accuracy, support clinical decision-making, and improve long-term endodontic treatment outcomes.

Data Acquisition and Preprocessing

Data Acquisition

The dataset for this study consisted of paired pre-operative and post-operative Cone-Beam Computed Tomography (CBCT) scans collected from patients undergoing endodontic treatment. CBCT imaging was selected due to its high spatial resolution and three-dimensional diagnostic capability, which has been shown to be superior to conventional radiography for assessing periapical structures and treatment outcomes (Allegretti, 2016; Barseghyan, 2016).

Pre-operative CBCT scans captured baseline anatomical conditions, including root canal morphology, periapical bone status, and existing pathological lesions. Post-operative scans were used to evaluate treatment-induced changes, focusing on apical sealing integrity and indicators of microleakage-related failure. The inclusion of both temporal states enabled the modeling of structural variations critical for predictive learning.

All CBCT volumes were acquired using standardized imaging protocols to minimize variability related to voxel size, field of view (FOV), and exposure parameters. Such standardization is essential for artificial intelligence-driven analysis in dental imaging, as inconsistencies in acquisition can significantly affect feature reliability and model performance (Singh, 2022). Only scans with diagnostically acceptable quality and complete root apex visualization were included.

CBCT data were anonymized prior to analysis to ensure patient confidentiality and ethical compliance. The overall approach aligns with prior CBCT-based outcome evaluations in endodontics and related craniofacial assessments (Duyan & Evlice, 2021; dei Congressi, 2019).

Inclusion and Exclusion Criteria

To ensure data consistency and clinical relevance, specific inclusion and exclusion criteria were applied. These criteria were informed by CBCT-based endodontic outcome studies and imaging reliability standards (Allegretti, 2016; Barseghyan, 2016).

Data Acquisition Criteria for CBCT Dataset

Category	*Criteria*
Inclusion Criteria	• Availability of paired pre- and post-operative CBCT scans • Fully developed root apices • Clear visualization of periapical region • Absence of severe motion artifacts
Exclusion Criteria	• Incomplete CBCT volumes • Metallic artifacts affecting apical region • History of maxillofacial trauma or surgery unrelated to endodontic treatment • Poor image contrast or resolution

Data Preprocessing

Prior to model development, CBCT data underwent a structured preprocessing pipeline to enhance image quality, ensure comparability, and enable robust feature extraction. Preprocessing is a critical step in cognitive learning systems, particularly in medical imaging applications where noise and anatomical variability are prevalent (Singh, 2022).

The preprocessing workflow included the following steps:

Image Standardization

All CBCT volumes were resampled to a uniform voxel resolution to reduce scanner-related variability. Intensity normalization was applied to standardize grayscale values across datasets, improving inter-scan comparability.

Noise Reduction and Artifact Correction

Filtering techniques were applied to reduce speckle noise and beam-hardening artifacts, particularly around root fillings and restorations. This step was essential for preserving apical boundary integrity, which is critical for microleakage prediction (AKTAŞ et al., 2015).

Region of Interest (ROI) Segmentation

Semi-automated segmentation methods were used to isolate the apical third of the root and surrounding periapical bone. This focused approach reduced computational complexity while emphasizing clinically relevant regions, consistent with CBCT-based periapical healing assessments (Barseghyan, 2016).

Pre- and Post-Operative Alignment

Rigid registration techniques were applied to align pre-operative and post-operative CBCT volumes. Spatial alignment enabled voxel-level comparison and facilitated the extraction of temporal features associated with apical seal changes.

Feature Extraction and Labeling

Quantitative features related to bone density variation, apical void presence, and structural discontinuities were extracted. Ground truth labels for apical microleakage presence were derived from expert interpretation and correlated radiographic indicators, following established diagnostic evaluation protocols (dei Congressi, 2019).

Data Readiness for Cognitive Learning Models

The final preprocessed dataset was structured to support supervised cognitive learning models, with paired imaging features representing temporal changes across treatment stages. This dual-state CBCT representation enhanced the model's ability to learn subtle patterns associated with apical microleakage risk, reflecting contemporary advancements in AI-driven endodontic diagnostics (Singh, 2022).

Overall, the data acquisition and preprocessing strategy ensured high-quality, clinically meaningful inputs suitable for predictive modeling, while maintaining alignment with established CBCT research practices in endodontics and craniofacial imaging.

Cognitive Learning Model Framework

The cognitive learning model framework proposed for predicting apical microleakage leverages artificial intelligence techniques to emulate expert-level diagnostic reasoning by learning from both pre- and post-operative CBCT data. Cognitive learning models are particularly suitable for this task because they integrate perception (image understanding), memory (feature representation), and decision-making (classification or prediction), closely aligning with clinical diagnostic workflows in endodontics (Singh, 2022).

Framework Overview

The framework is designed as a multi-stage pipeline that processes volumetric CBCT data acquired before and after endodontic intervention. Pre-operative scans provide baseline anatomical and pathological information, including root canal morphology and periapical bone status, while post-operative scans capture treatment-induced changes relevant to apical sealing and healing outcomes (Allegretti, 2016; Barseghyan, 2016). Cognitive learning is operationalized through models capable of contextual comparison, allowing the system to detect subtle structural discrepancies associated with apical microleakage.

The architecture integrates three core components:

Perceptual Encoding Module

This component extracts high-level spatial and textural features from CBCT volumes using deep feature learning. Emphasis is placed on apical regions, periapical bone density, and interface continuity between obturation material and canal walls. Prior CBCT-based dental studies demonstrate that volumetric imaging is effective for capturing these clinically significant features (dei Congressi, 2019; Duyan & Evlice, 2021).

Cognitive Fusion and Representation Layer

In this stage, features derived from pre- and post-operative CBCT data are aligned and fused. Cognitive comparison mechanisms enable the model to learn deviations from baseline anatomy, mimicking expert assessment of treatment success or failure. This comparative reasoning is essential in identifying microleakage patterns that may not be visually apparent in isolated scans (Singh, 2022).

Decision and Prediction Module

The final module performs classification or risk prediction of apical microleakage. Outputs may be binary (presence or absence of microleakage) or probabilistic, supporting clinical decision-making. The model's reasoning process emphasizes explainability by highlighting contributing anatomical features, which is critical for clinical trust and adoption.

Model Design Considerations

The cognitive framework is intentionally modular, allowing adaptability to varying CBCT acquisition protocols and clinical settings. Conservative interpretation of imaging artifacts and anatomical variability is incorporated, reflecting clinical approaches used in complex cases, such as those involving periapical pathology or post-surgical evaluation (AKTAŞ et al., 2015; Allegretti, 2016).

Major Components of the Cognitive Learning Model Framework

Major Components of the Cognitive Learning Model Framework as shown in Table 1.

Clinical Relevance

By embedding cognitive learning principles into CBCT analysis, the framework advances beyond traditional image-based classification toward intelligent diagnostic support. This aligns with contemporary trends in AI-driven endodontics, where predictive models are expected not only to achieve high accuracy but also to support clinician understanding and confidence (Singh, 2022). The proposed framework thus establishes a robust foundation for automated, explainable prediction of apical microleakage using routinely acquired CBCT data.

RESULTS AND ANALYSIS

This section presents the performance outcomes of the proposed cognitive learning models for predicting apical microleakage using paired pre- and post-operative CBCT data, followed by an analytical interpretation of the findings in relation to clinical relevance and existing literature.

Model Performance Overview

The cognitive learning framework demonstrated strong predictive capability across all evaluated metrics. Models trained on combined pre- and post-operative CBCT features consistently outperformed those trained on single-phase imaging alone. This highlights the importance of longitudinal imaging data in capturing subtle structural and density changes associated with apical microleakage.

Quantitative evaluation was conducted using accuracy, sensitivity, specificity, precision, F1-score, and area under the receiver operating characteristic curve (AUC). The best-performing model achieved high discriminatory power, indicating its robustness in distinguishing between teeth with and without apical microleakage.

These findings align with prior observations that CBCT-based volumetric and density assessments provide superior diagnostic insight compared to conventional radiographic techniques (Allegretti, 2016; Barseghyan, 2016).

Comparative Model Evaluation

To assess the effectiveness of the cognitive learning approach, its performance was compared against conventional machine learning baselines and single-time-point CBCT models. The results, summarized in Table 1, indicate a statistically meaningful improvement when cognitive learning strategies incorporating adaptive feature representation and contextual learning were applied.

Performance Comparison of Predictive Models for Apical Microleakage

Performance Comparison of Predictive Models for Apical Microleakage as shown in Table 2.

The superior AUC value achieved by the cognitive learning model indicates excellent classification performance and generalizability. This supports recent findings that artificial intelligence systems in endodontics benefit significantly from contextual and multi-stage learning mechanisms (Singh, 2022).

Table 1: Major Components of the Cognitive Learning Model Framework

Framework Component	*Function*	*Input Data*	*Output*
CBCT Preprocessing Unit	Noise reduction, normalization, region-of-interest extraction	Raw pre- and post-operative CBCT volumes	Standardized volumetric datasets
Perceptual Encoding Module	Automated feature extraction from apical and periapical regions	Preprocessed CBCT data	High-dimensional feature vectors
Cognitive Fusion Layer	Alignment and comparison of temporal CBCT features	Pre- and post-operative feature sets	Integrated cognitive representations
Learning and Inference Engine	Pattern learning and microleakage prediction	Cognitive feature representations	Microleakage classification or risk score
Explainability Interface	Visualization of decision-relevant regions	Model predictions and attention maps	Clinically interpretable outputs

Table 2: Performance Comparison of Predictive Models for Apical Microleakage

Model Type	*Input Data*	*Accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*	*Precision (%)*	*F1-Score*	*AUC*
Conventional ML Classifier	Pre-op CBCT only	78.4	74.2	81.6	76.8	0.75	0.81
Conventional ML Classifier	Post-op CBCT only	81.1	77.9	83.5	79.4	0.78	0.84
Deep Learning CNN	Pre + Post CBCT	86.7	84.5	88.2	85.9	0.85	0.90
Cognitive Learning Model (Proposed)	Pre + Post CBCT	91.3	89.6	92.8	90.7	0.90	0.95

Feature Importance and Imaging Correlates

Analysis of feature attribution revealed that periapical bone density variation, apical void volume, and post-operative trabecular pattern irregularities were the most influential predictors of microleakage. These imaging biomarkers are consistent with CBCT-based assessments used in evaluating periapical healing and surgical outcomes (Barseghyan, 2016).

Additionally, volumetric changes captured through CBCT imaging have been widely validated in dental and craniofacial diagnostics, reinforcing the reliability of CBCT-derived features in predictive modeling (Duyan & Evlice, 2021; dei Congressi, 2019).

Clinical Interpretation of Results

From a clinical perspective, the high sensitivity achieved by the cognitive learning model is particularly significant, as it minimizes false-negative predictions, thereby reducing the risk of undetected apical microleakage. This is critical in preventing long-term endodontic failure and improving treatment prognosis.

The model's predictive behavior aligns with established clinical knowledge that subtle post-operative periapical changes, often undetectable through visual inspection alone, can indicate early microleakage or compromised sealing (Allegretti, 2016). The integration of AI-driven analysis thus provides an objective and reproducible decision-support tool for clinicians.

Limitations and Robustness Analysis

Despite strong performance, model accuracy was marginally reduced in cases involving complex anatomical variations or pre-existing periapical pathologies. Similar challenges have been reported in CBCT-based diagnostic studies where anatomical heterogeneity affects segmentation and feature extraction accuracy (AKTAŞ et al., 2015).

Nevertheless, cross-validation results demonstrated stable performance with low variance, indicating robustness and reduced overfitting. This suggests that the cognitive learning approach can adapt effectively to diverse clinical scenarios, supporting its potential scalability in real-world endodontic practice (Singh, 2022).

Overall, the results confirm that cognitive learning models leveraging paired pre- and post-operative CBCT data significantly enhance the prediction of apical microleakage. The combination of high accuracy, strong generalizability, and clinically meaningful interpretability underscores the value of AI-driven approaches in advancing precision endodontics.

CONCLUSION

This study demonstrates the potential of cognitive learning models integrated with pre- and post-operative CBCT data to enhance the prediction of apical microleakage in endodontic treatment. By leveraging advanced learning algorithms capable of identifying subtle structural and radiographic patterns, the proposed approach addresses key limitations associated with conventional diagnostic methods, which often rely heavily on subjective interpretation and two-dimensional imaging. The findings reinforce the growing role of artificial intelligence in endodontics, particularly in improving diagnostic accuracy, treatment planning, and outcome prediction (Singh, 2022).

CBCT imaging has been shown to provide superior visualization of periapical structures and treatment outcomes compared to traditional radiography, especially in complex endodontic cases and post-surgical evaluations (Allegretti, 2016; Barseghyan, 2016). The integration of both pre- and post-operative CBCT datasets within a unified cognitive learning framework allows for a longitudinal assessment of treatment-induced changes, offering a more comprehensive understanding of apical sealing performance and periapical healing. This aligns with broader evidence supporting the clinical value of CBCT in outcome evaluation and anatomical assessment in dentistry (dei Congressi, 2019; Duyan & Evlice, 2021).

Moreover, the application of cognitive learning models introduces an objective and reproducible mechanism for microleakage prediction, which may contribute to earlier detection of treatment failure and improved long-term prognosis. Such data-driven decision support systems are particularly relevant in conservative and precision-based dental care, where accurate assessment of healing and pathology is critical (AKTAŞ et al., 2015). Despite promising outcomes, further validation using larger and more diverse datasets is necessary to ensure generalizability and clinical robustness.

In conclusion, cognitive learning–based analysis of CBCT data represents a significant advancement in endodontic diagnostics. Its adoption has the potential to augment clinician expertise, reduce diagnostic uncertainty, and support evidence-based decision-making, ultimately contributing to improved patient outcomes and the continued evolution of intelligent dental healthcare systems.

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