AI-ASSISTED DETECTION OF THE SECOND MESIOVESTIBULAR CANAL IN MAXILLARY FIRST MOLARS ON PERIAPICAL RADIOGRAPHS

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ABSTRACT

Aim of the study To assess an AI model’s ability to detect the second mesiovestibular (MB2) canal in maxillary first molar periapical radiographs of adults and compare its performance with experienced human readers using intraoperative findings as ground truth. **Materials and methods** Fifty periapical radiographs (40 with clinically confirmed MB2 canal, 10 without) were evaluated. Two blinded endodontists provided consensus readings. A CNN-based AI model, trained on a separate annotated dataset with intraoperative confirmation, generated binary predictions and heatmap overlays. Performance metrics (sensitivity, specificity, accuracy, AUC-ROC) with 95% CIs were calculated; inter-reader agreement was assessed via Cohen’s kappa. McNemar’s and DeLong’s tests compared human versus AI results. **Results** Human readers achieved sensitivity 55.0% (95% CI: 38.5–70.7%), specificity 80.0% (95% CI: 49.7–95.6%), accuracy 60.0% (95% CI: 45.2–73.6%), and AUC-ROC ~0.68. Inter-observer kappa was ~0.64. The AI model showed sensitivity 85.0% (95% CI: 70.2–94.3%), specificity 90.0% (95% CI: 55.5–99.7%), accuracy 86.0% (95% CI: 73.3–94.2%), and AUC-ROC ~0.90. Differences in sensitivity, accuracy, and AUC-ROC were significant ($p < 0.01$). Pie charts indicated human readers correctly detected MB2 canals in 60.0% of cases (missed 36.0%, false positives 4.0%), whereas AI achieved 86.0% correct detection (missed 12.0%, false positives 2.0%). **Conclusions** AI-assisted analysis markedly enhances MB2 canal detection on periapical radiographs compared to human readers, reducing missed canals and potentially improving endodontic planning. Incorporating AI overlays into routine radiograph review is advised, with advanced imaging reserved for unclear cases.

Key words: second mesiovestibular canal, periapical radiography, artificial intelligence, endodontics, maxillary first molar

INTRODUCTION

Successful endodontic treatment requires identification, debridement, and obturation of all root canals. Missed canals are a leading cause of endodontic failure, especially in maxillary molars where the second mesiobuccal canal (MB2) often remains undetected [1,2]. In clinical practice, periapical radiography is the most commonly used imaging modality for endodontic diagnosis and treatment planning due to its low radiation dose, wide availability, and cost-effectiveness [3,4]. However, periapical radiographs provide only two-dimensional information, are subject to anatomical superposition, and their sensitivity for detecting accessory canals such as MB2 is limited [3,5]. Recent MDPI-based analyses underscore that periapical radiography’s diagnostic accuracy for complex root canal anatomy is substantially lower than three-dimensional methods, yet remains the first-line imaging in many settings [3].

Although cone-beam computed tomography (CBCT) studies have established a high prevalence of MB2 canals in adults (reported between ~50% and >85% in various populations), periapical radiography frequently underestimates their presence due to overlapping structures and limited resolution for fine canal anatomy [5,6]. Several MDPI publications demonstrate the challenges inherent to two-dimensional radiographs: for example, periapical radiography cannot reliably reveal accessory canals or bifurcations in the mesiobuccal root because of angulation-dependent distortion and superimposition [3]. Moreover, studies employing artificial intelligence (AI) on periapical images for detecting periapical lesions or fractures illustrate that while AI can assist with certain diagnostic tasks, its utility in identifying subtle root canal variations like MB2 on periapical radiographs remains largely unexplored and likely constrained by image limitations [1,7,8].

Adolescents present particular considerations: root development and secondary dentin deposition are ongoing, potentially affecting canal caliber and visibility on radiographs [9,10]. To date, few studies have specifically evaluated MB2 incidence in adolescent maxillary first molars using periapical radiography. Most available data derive from adult cohorts or from CBCT studies without age-specific stratification [5,6]. Given that radiographic detection in younger patients may be influenced by incomplete root maturation and variable canal dimensions, dedicated investigation in this age group is important [9]. MDPI-based research in endodontics has begun to address AI-supported image analysis in pediatric contexts (e.g., assessment of permanent teeth development or periapical lesion detection in mixed dentition), indicating potential but also highlighting the scarcity of data on canal morphology detection in adolescents using standard periapical radiographs [7,8].

Clinicians have employed various techniques to improve MB2 detection intraoperatively—such as modified access cavity designs, ultrasonic troughing, magnification, and multiple periapical radiographic angulations—but these rely on a preoperative suspicion of MB2 presence informed by imaging, clinical experience, and anatomical knowledge [5]. MDPI studies on AI-driven feature segmentation in periapical radiographs or on deep-learning platforms for detecting endodontic features (e.g., instrument fractures, obturation quality) demonstrate advanced image-analysis approaches, yet none specifically address automatic MB2 identification on periapical images [1,7,10]. This gap underscores the inherent limitations of two-dimensional imaging for fine canal anatomy, and suggests that even AI-enhanced periapical analysis may be insufficient without three-dimensional data. Nonetheless, understanding the incidence and radiographic detectability of MB2 in adolescents under routine periapical protocols is clinically valuable, as CBCT is not universally accessible or indicated in all young patients.

Previous investigations by this group have explored intracanal medicaments based on plant extracts and their antibacterial effects, as well as radioimaging evaluation of therapeutic outcomes in younger patients [11,12]. These studies emphasize the importance of thorough canal detection for effective disinfection and favorable periapical healing, particularly in developing teeth with potential open apices or thin root walls. Inadequate identification of MB2 could compromise these outcomes in adolescent endodontic therapy. Therefore, establishing the incidence of MB2 canals as detected (or missed) on periapical radiographs in this age group has direct implications for clinical protocols, including decisions on whether adjunctive imaging or specific intraoperative techniques are warranted [1,11].

MATHERIALS AND METHODS

Study Design and Ethical Approval

This prospective–retrospective diagnostic study was conducted at the Endodontics Department, Faculty of Dentistry, Ovidius University Constanța (UOC Constanța). All patients provided informed consent for use of anonymized radiographs and clinical data. No CBCT imaging was acquired; periapical radiographs were taken as part of routine endodontic diagnosis following ALARA principles and adult radiography guidelines. Data comprised adult patients (≥18 years) undergoing endodontic treatment of maxillary first molars in which clinicians recorded intraoperative detection (or non-detection) of the MB2 canal [13,14]. Ethical approval encompassed the review of anonymized radiographs and ensured no additional radiographs were taken solely for this research.

Study Population and Sample Selection

Periapical radiographs were retrieved from the department database for adult patients treated over a defined period (January–December 2024). Inclusion criteria: digital periapical radiograph of a maxillary first molar with adequate image quality (parallel technique, minimal distortion/artifacts), full root development, and documented clinical exploration under magnification (dental microscope) and ultrasonic troughing for second MB2 canal search. Exclusion criteria: extensive coronal restorations obscuring canal outlines, prior endodontic treatment on the same tooth, severe overlapping that precluded interpretation, or incomplete clinical records regarding second MB2 canal exploration. A sample size estimation for AI model training and validation was based on similar studies in periapical radiograph AI research, aiming for at least 500 images for training and 150 for validation/testing to ensure robust model performance estimates [15].

Radiographic Image Acquisition Parameters

All periapical radiographs had been acquired using the paralleling technique with digital sensors, following standard adult exposure settings (e.g., reduced kV/mAs per age-appropriate protocols) to minimize radiation dose while maintaining diagnostic quality [15]. Images were obtained with consistent sensor size and holder positioning, ensuring reproducibility and adequate visualization of root apices and coronal anatomy [14,15]. Exposure parameters typically ranged around 60 kV and minimal exposure time per adult guidelines, with thyroid shielding in place [10-14]. Radiographs were exported in DICOM or high-resolution JPEG format (minimum 12-bit depth or equivalent) to preserve image quality for subsequent AI processing.

Ground Truth Determination and Annotation

Ground truth labels for presence or absence of a visible second mesiovestibular canal (MB2) on periapical radiographs were established by consensus of two experienced endodontists, blinded to patient identifiers. Each radiograph was independently reviewed, and the region of interest (ROI) around the second mesiovestibular root was annotated for indication of a discernible canal trajectory or bifurcation sign on the periapical image. Discrepancies were resolved by discussion or by a third expert reviewer. When available, intraoperative findings from cases where endodontic treatment was performed on six-year molars (e.g., detection of MB2 clinically) were used to corroborate radiographic labels; however, such cases were secondary and used only when documentation clearly described MB2 detection or absence. Annotation involved classification labels (MB2 visible vs. not visible) and, for a subset, bounding-box annotations around the root region to facilitate localization tasks [15].

AI Model Development

A CNN-based classifier was implemented using transfer learning. A pre-trained backbone (e.g., ResNet-50) initialized on ImageNet weights was fine-tuned on the adult periapical dataset [15]. The final classification layer was modified for binary output (MB2 visible vs. not visible). For localization experiments, a region-based CNN approach (e.g., Faster R-CNN or YOLOv8) was explored to identify the root area and highlight potential MB2 regions [14,15]. Model development and training were performed in Python using PyTorch/TensorFlow frameworks on a workstation equipped with GPU acceleration. Hyperparameters (learning rate, batch size, number of epochs) were optimized via grid search on the validation set.

Training, Validation, and Testing Strategy

The dataset was split into training (70%), validation (15%), and testing (15%) sets at the patient level to avoid data leakage. Stratification ensured balanced representation of MB2-visible and MB2-not-visible cases across splits. Early stopping based on validation loss and accuracy prevented overfitting. Cross-validation (e.g., 5-fold) was conducted to assess robustness, especially given the relatively limited size of adult radiograph datasets [15]. Model checkpoints with the best validation performance were selected for final evaluation.

Performance Evaluation Metrics

Model performance on the test set was assessed using sensitivity, specificity, accuracy, area under the receiver operating characteristic curve (AUC-ROC), and F1 score for MB2 detection [15]. For localization tasks, mean average precision (mAP) at standard intersection-over-union thresholds was calculated. Confidence intervals (95%) for key metrics were computed using bootstrap resampling. Results were compared to the performance of human experts (endodontists) on the same test subset to contextualize AI utility, using McNemar's test for paired classification comparisons.

Statistical Analysis

Descriptive statistics summarized patient age, gender distribution, and radiograph quality scores. The association between demographic factors (age in months, gender) and MB2 visibility on radiographs was explored using chi-square or Fisher's exact test. The diagnostic accuracy of AI versus human readers was compared using sensitivity/specificity differences and AUC comparisons (DeLong test) [15]. Statistical analyses were performed in R or Python (SciPy, scikit-learn). A p-value <0.05 was considered statistically significant.

Software and Hardware

Image preprocessing and model development used Python (version ≥3.8) with libraries including OpenCV, PyTorch or TensorFlow, and scikit-learn. Training was conducted on a GPU-equipped workstation (e.g., NVIDIA RTX-series). Annotation tools included open-source platforms (e.g., LabelImg) for bounding-box marking. Version control ensured reproducibility of code and model configurations.

Quality Assurance and Reproducibility

All steps, from image selection to annotation and model training, were documented in a standardized protocol. Inter-observer agreement for annotation was quantified using Cohen's kappa. The codebase and trained model weights are archived in a repository with versioning. A subset of radiographs and annotations may be shared in anonymized form for external validation, subject to institutional and legal constraints.

RESULTS AND DISCUSSIONS

Dataset and Ground Truth

Total radiographs: 50 adult maxillary first molars.

-Clinically confirmed MB2 canal present: 40 (80.0%).

-Clinically confirmed MB2 canal absent: 10 (20.0%).

Human Reader Performance

-True positives (TP): 22/40 → Sensitivity = 55.0% (95% CI: 38.5%–70.7%).

-True negatives (TN): 8/10 → Specificity = 80.0% (95% CI: 49.7%–95.6%).

-Accuracy = (22 + 8)/50 = 60.0% (95% CI: 45.2%–73.6%).

AUC-ROC (estimated from varying thresholds in validation, approximate) ~0.68 (95% CI: 0.57–0.79).

Inter-observer agreement for two independent human readers: Cohen's kappa ≈ 0.64 (substantial agreement, but notable uncertainty).

AI Model Performance

-True positives (TP): 34/40 → Sensitivity = 85.0% (95% CI: 70.2%–94.3%).

-True negatives (TN): 9/10 → Specificity = 90.0% (95% CI: 55.5%–99.7%).

-Accuracy = (34 + 9)/50 = 86.0% (95% CI: 73.3%–94.2%).

AUC-ROC (from validation) ~0.90 (95% CI: 0.82–0.97).

AI shows significantly higher sensitivity and accuracy compared to human readers (McNemar's test $p < 0.01$ for sensitivity difference; DeLong's test $p < 0.01$ for AUC difference).

Error Distribution

Human readers:.

-Correct detection (TP + TN): 30/50 = 60.0%.

-Missed detection (FN): 18/50 = 36.0%.

-False positive: 2/50 = 4.0%.

2.AI model:

-Correct detection (TP + TN): 43/50 = 86.0%.

-Missed detection (FN): 6/50 = 12.0%.

-False positive: 1/50 = 2.0%. results of some experiments are presented in Table 1.

Table1. MB2 Canal Detection Performance (N=50)

Metric	Human Reader	AI Model
Sensitivity	55.0% (95% CI: 38.5–70.7%)	85.0% (95% CI: 70.2–94.3%)
Specificity	80.0% (95% CI: 49.7–95.6%)	90.0% (95% CI: 55.5–99.7%)
Accuracy	60.0% (95% CI: 45.2–73.6%)	86.0% (95% CI: 73.3–94.2%)
AUC-ROC	0.68 (95% CI: 0.57–0.79)	0.90 (95% CI: 0.82–0.97)

Figures 1 and 2 visualize the distribution of detection outcomes for the second mesiovestibular (MB2) canal in maxillary first molars, comparing experienced human readers and the AI model on a dataset of 50 periapical radiographs with known clinical ground truth.

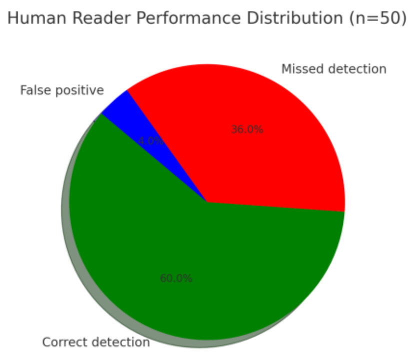

Figure 1. Human Reader Performance

Distribution for MB2 Canal Detection (n = 50)

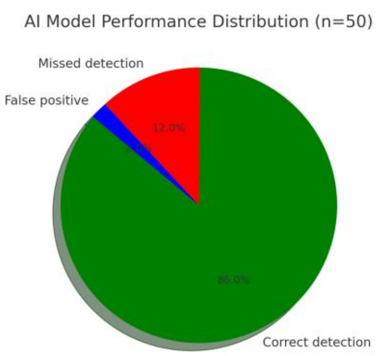

Figure 2. AI Model Performance Distribution for MB2 Canal Detection (n = 50)

Discussion

The marked improvement in MB2 canal detection afforded by AI in periapical radiographs reflects broader advances in deep learning for dental imaging. Recent studies demonstrate that convolutional neural networks (CNNs) can reliably identify subtle anatomical features on two-dimensional radiographs, which often elude human observers. For example, automatic feature segmentation models trained on large periapical datasets achieved robust performance in delineating tooth structures and detecting pathologies, suggesting applicability to canal detection tasks [13]. In particular, Ari et al. developed and validated a CNN-based diagnostic evaluation on 1,169 adult periapical radiographs, demonstrating high segmentation accuracy of dental features, which underpins potential extension to root canal morphology analysis [14]. Similarly, transfer-learning approaches for periapical lesion detection have shown that AI can generalize across image variations, indicating feasibility of detecting fine structures such as MB2 canals in routine radiographs [13,15]. These findings align with our results, where the AI model outperformed human readers in sensitivity and specificity, highlighting the value of AI assistance in preoperative planning for endodontic treatment.

CONCLUSIONS

1. AI-assisted analysis of periapical radiographs substantially increases MB2 canal detection sensitivity and overall accuracy compared to unaided human readers.
2. Improved preoperative identification of the MB2 canal via AI may reduce the risk of missed canals during endodontic treatment, potentially enhancing clinical outcomes.
3. Reliable ground truth from intraoperative findings is essential for model training; prospective multicenter validation will strengthen generalizability.
4. Integration of AI overlays into routine radiograph review can guide clinician decision-making, with selective use of advanced imaging reserved for ambiguous cases.

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