AI-Assisted Tool for Assessing Quality of Final Root Canal Treatment Using Dental Radiographs: A Review

R.A.J.C. Adhikari*, A.M.K.M. Adikari*, D.M.G.S. Dassanayake*, R.D. Jayasinghe†,
I. Nawinne*, R. Ragel*, R.M.S. G.K. Rasnayake‡, R.M. Jayasinghe‡, M.C.N. Fonseka§, P.A. Hewage§
*Dept. of Computer Engineering, Faculty of Engineering, University of Peradeniya, Sri Lanka
†Dept. of Oral Medicine and Periodontology, Faculty of Dental Sciences, University of Peradeniya, Sri Lanka
‡Dept. of Prosthetic Dentistry, Faculty of Dental Sciences, University of Peradeniya, Sri Lanka
§Dept. of Restorative Dentistry, Faculty of Dental Sciences, University of Peradeniya, Sri Lanka
e19008@eng.pdn.ac.lk, e19009@eng.pdn.ac.lk, e19063@eng.pdn.ac.lk, ruwanja@dental.pdn.ac.lk,
isurunawinne@eng.pdn.ac.lk, roshanr@eng.pdn.ac.lk, srasnayaka@dental.pdn.ac.lk, manorija@dental.pdn.ac.lk,
manchris@pdn.ac.lk, pahewage@gmail.com

***Abstract*—Root canal treatment is crucial for preserving teeth compromised by severe decay, infection, or trauma. Evaluating final treatment quality, which depends on factors such as root canal filling length, the presence of voids, and the integrity of the lateral seal, is vital for preventing reinfection and ensuring long-term tooth survival. Traditionally, periapical radiographic assessment by clinicians has been the primary evaluation method; however, subjective judgment, variability in expertise, and suboptimal imaging conditions can lead to inconsistent outcomes. Recent advances in artificial intelligence offer promising pathways for improving and standardizing root canal treatment assessments. Deep learning, especially convolutional neural networks, has shown robust performance in detecting, classifying, and segmenting dental structures on periapical radiographs. Studies indicate that segmentation-based approaches can significantly enhance measurement accuracy for root canal filling length and other critical quality parameters. This review provides a comprehensive overview of the essential root canal treatment quality metrics, highlights the limitations of manual periapical radiographic evaluation, and examines the latest AI-driven methods, including data preprocessing, model architectures, and annotation techniques, designed for root canal treatment quality assessment.**

***Index Terms*—Root Canal Treatment, Dental Radiographs, Artificial Intelligence, Deep Learning, Convolutional Neural Networks, Quality Assessment, Endodontics, Image Segmentation**

I. Introduction

Root canal treatment (RCT) is a dental procedure that is frequently performed and is intended to preserve teeth that have been compromised by severe decay, infection, or trauma [1]. The primary objective of RCT is to prevent reinfection, eliminate infection from the root canal system, and guarantee the long-term functionality of the treated tooth [2]. This process involves the meticulous cleansing and shaping of the root canal, which is subsequently sealed with a biocompatible material to prevent bacterial infiltration [2]. The success of RCT is crucial for the longevity of teeth, as inadequate treatment can lead to complications such as periapical lesions, persistent pain, and eventual treatment failure [3]. Given these risks, the accurate assessment of RCT quality is essential, as this evaluation directly impacts treatment outcomes and informs subsequent clinical interventions when necessary [1].

Radiographic imaging is essential for the assessment of the quality of RCT, as it provides a comprehensive visual representation of critical parameters, including the length of the root canal filling, the presence of voids, the integrity of the lateral closure, and the extension of the apical region [4]. Periapical radiographs, in particular, are frequently used to assess whether the root canal filling is complete, extends to the correct length, and exhibits proper sealing. These evaluations are essential in determining the technical success of the procedure and ensuring that the treatment meets established clinical standards. However, while radiographic evaluation is indispensable in RCT assessment, it is not without its limitations [2].

Manual interpretation of radiographs presents several challenges, primarily due to its inherent subjectivity. Evaluations often vary based on the clinician's experience, training, and visual acuity, leading to inconsistencies in assessment [5]. Additional factors such as variations in lighting conditions, radiographic image quality, and the limitations of two-dimensional imaging further contribute to discrepancies. Traditional radiographs provide only a two-dimensional representation of a complex three-dimensional root canal system, making it difficult to accurately assess the spatial relationship between the filling material and the canal walls [2]. To mitigate these issues, it is important that radiographs are taken with consistent parameters and clinicians should make an effort to standardise their approach to interpreting radiographs [6].

To enhance the reliability of RCT evaluation, standardization in radiographic interpretation and adherence to consistent imaging parameters are crucial. However, given the persistent challenges of human interpretation, there is increasing interest in using artificial intelligence (AI) for more objective, accurate, and standardized assessment of RCT quality [7]. AI-driven models have shown promise in automating radiographic interpretation, reducing variability, and improving diagnostic precision [8]. As advancements in AI-based dental imaging continue, these technologies hold the potential to transform the evaluation of RCT outcomes, offering a more robust and reliable alternative to traditional manual assessment.

II. Quality Assessment of Root Canal Treatment

The success of RCT is highly dependent on the quality of the procedure, as inadequate treatment can lead to reinfection, persistent pain, and eventual tooth loss. To ensure a favorable prognosis, dental professionals assess RCT quality using a combination of clinical evaluation and radiographic analysis [9]. However, the reliability of these assessments can vary due to subjectivity in interpretation and inconsistencies in evaluation criteria. Establishing standardized parameters for quality assessment is therefore essential for improving treatment outcomes and guiding clinical decision-making.

Several key parameters are crucial in determining the success of a root canal treatment.

A. Root Canal Filling Length

The length of the root canal filling is a critical factor in the success of RCT [10]. Ideally, the filling should extend to within 0.5 to 2 mm of the radiographic apex, which approximates the location of the apical constriction. This distance is considered optimal for achieving a complete seal of the root canal system without overextension into the periapical tissues [11].

- **Underfilling**, where the root canal filling terminates too far from the apex, may leave residual bacteria and infected tissue in the apical portion of the canal, which can lead to persistent infection and treatment failure. This is because the unfilled space can act as a reservoir for bacteria, preventing complete disinfection and promoting reinfection. Studies show that root fillings ending more than 2 mm from the radiographic apex have a lower success rate [9]. As seen in Fig. 1, underfilled canals leave a significant portion of the root untreated, increasing the risk of reinfection.

Fig. 1. A radiograph showing an underfilled root canal.

- **Overfilling**, where the filling material extends beyond the radiographic apex, can cause irritation and inflammation in the periapical tissues, resulting in postoperative pain and delayed healing. The extruded material can act as a foreign body and may interfere with the natural healing process, potentially leading to treatment failure [12]. Overfilling has been shown to have the lowest success rate, especially when a preoperative apical area is present [10]. The literature suggests that both overfilling and underfilling can compromise the outcome of RCT and that the most successful fillings terminate at the ideal length. As seen in Fig. 2, overextended filling material can provoke an inflammatory response, leading to discomfort and prolonged healing time.

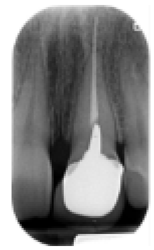

Fig. 2. A radiograph showing an overfilled root canal.

B. Presence of Voids

Voids are defined as empty spaces or gaps within the root filling material. They compromise the seal and increase the risk of bacterial leakage and re-infection. A high-quality RCT should have a homogeneous and dense filling, which is free of visible voids or gaps [13].

The presence of voids indicates that the filling material has not adequately filled the canal space and created a hermetic seal. These voids provide a space where bacteria can accumulate and proliferate, even if the canal was disinfected during treatment. This significantly reduces the long-term success of the treatment [11]. As shown in Fig. 3, voids within the root filling disrupt the uniformity of the seal, creating potential entry points for microbial contamination.

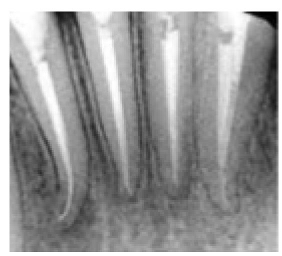

Fig. 3. A radiograph showing voids within the root canal filling.

The density of the filling material also reflects the quality of the seal. A homogeneous, dense filling ensures that there are no pathways for bacterial ingress [5]. However, the identification of voids can be challenging using conventional two-dimensional (2D) periapical radiographs, as overlapping structures may obscure their visibility.

C. Lateral Seal Quality

The quality of the lateral seal refers to how tightly the filling material adheres to the canal walls. A proper lateral seal is essential to prevent microleakage [9], which is the passage of fluids and bacteria along the interface between the canal wall and the filling material. Microleakage can lead to persistent infection and treatment failure [9].

An inadequate lateral seal may result from improper canal shaping or poor adaptation of the obturation material to the canal walls [13]. The effectiveness of the lateral seal depends on both the technique used and the operator's experience.

A tight lateral seal, where the filling material adheres closely to the canal walls, helps prevent bacterial colonization and ensures the long-term success of the treatment. Studies have shown that a poor lateral seal is a significant contributor to RCT failure, making it crucial to select obturation materials and techniques that provide an effective seal [9].

D. Absence of Procedural Errors

The absence of technical errors during root canal preparation is an important indicator of the quality of the treatment. Procedural errors can compromise the ability to adequately disinfect the canal, and create ledges, or other areas that can harbor bacteria, and make adequate obturation difficult [10].

Common procedural errors include:

1) Missed Canals: One important reason why root canal therapy fails is missed canals. This happens when a dentist fails to identify and treat every canal in a tooth's root system [14]. This is particularly problematic in teeth with multiple roots since the likelihood of untreated gaps is increased by complex canal structure.

Impact on Treatment:

- Missed canals can act as bacterial reservoirs, resulting in long-term illness [15].
- The presence of an untreated canal is associated with significantly higher rates of apical periodontitis and treatment failure, with failure rates observed to be 6.25 times greater in untreated canals and a 4.38 times higher likelihood of unsuccessful outcomes when a canal is missed [15].

2) Separated Instruments: Separated instruments (SIs) are a challenging complication that can occur during root canal therapy. When an endodontic file or other instrument fragment breaks inside the root canal, it can cause instrument separation, which makes it more difficult to clean, shape, and obturate the canal system [16]. A separated instrument may result in treatment failure if improperly handled. As shown in Fig. 4, the presence of a separated instrument can obstruct the canal, preventing adequate disinfection and increasing the risk of persistent infection.

Impact on Treatment:

- SIs can obstruct further cleaning and shaping of the canal, preventing complete debridement and obturation [16].
- Periapical healing success rates may be considerably decreased by the existence of a detached instrument, particularly in cases where apical pathosis already exists [2].
- The point at which instrument separation occurs in respect to the level of prior canal disinfection may influence the treatment outcome [2].

Fig. 4. A radiograph showing voids within the root canal filling.

To ensure consistency in the evaluation of root canal treatment quality, various professional organizations have established guidelines that provide standardized assessment criteria. By following these guidelines, physicians can maintain a high standard of care while achieving predictable and successful treatment outcomes.

- **The European Society of Endodontology (ESE):** The ESE provides comprehensive guidelines for endodontic treatment, and they also include specific criteria for evaluating the quality of root canal fillings. These criteria include that the filling should be homogenous and free of internal and external voids and that the root canal filling should terminate between 0.5 and 2.0 mm from the radiographic apex [17]. The ESE has also established guidelines for the assessment of root canal treatment quality through radiographic means.
- **The American Association of Endodontists (AAE):** The AAE recommends radiographic examination as a part of the routine assessment of root canal treatment, and it provides guidelines for the technical aspects of treatment, including obturation. The AAE also provides benchmarks for acceptable root canal treatment, including fill length, the absence of voids, and a tapered shape [13].

By following these guidelines, clinicians can ensure that their treatment approach aligns with best practices, ultimately improving patient outcomes and reducing the risk of treatment failure.

III. Challenges in Radiographic Assessment of RCT

Radiographic assessment is an important part of evaluating the quality of RCT, but manually evaluating them presents several challenges including variability in clinician interpretation, differences in image quality, and the inherent difficulty in detecting treatment deficiencies such as voids, underfilling, or overfilling.

A. Inter-Clinician Variability and Subjectivity

One of the most significant challenges in the radiographic evaluation of RCT is subjectivity in interpretation. The same radiograph may be evaluated differently by different clinicians depending on their expertise and experience. Studies have shown that variations exist among dental students, general dentists, and endodontists when evaluating root canal treatments [11].

Factors Contributing to Variability

- **Experience and Training Level:** Because of their specific training in radiographic analysis, endodontists are more likely than general practitioners to identify treatment failings. Research indicates that endodontists tend to rate the quality of root canal fillings higher than radiologists [11]. This suggests that expertise influences evaluation accuracy, but even among specialists, differences in interpretation persist.
- **Personal Bias and Focus Areas:** Unconsciously, clinicians could pay attention to some parts of the radiograph while ignoring others. For example, some may prioritize on determining the root filling's length, while others might pay more attention to its density or taper [10]. This selective attention can lead to inconsistent evaluations and potential misdiagnosis of treatment quality.

B. Image Quality and Radiographic Limitations

The quality of radiographic images significantly impacts the accuracy of RCT assessments. Several factors can compromise image quality, making it challenging for clinicians to perform precise evaluations. Poor image quality can cover important details, increasing the risk of misinterpretation and inaccurate treatment assessments.

Factors Affecting Radiographic Image Quality

- **Lighting Conditions:** Proper lighting is crucial for accurate interpretation. It might be challenging to identify small voids, overfillings, or small anatomical differences while viewing radiographs under less than ideal lighting conditions because fine details are hidden [6].
- **Contrast and Resolution:** Image contrast and resolution play a major role in distinguishing root infill materials from surrounding structures. It may be challenging to differentiate the filling material from tooth structures in periapical radiographs due to low contrast or poor resolution [18], which could result in mistakes while detecting voids or identifying the filling's position relative to the apex.
- **Angulation and Projection Errors:** Radiographs provide a 2D representation of a three-dimensional (3D) structure, which can introduce distortions and misinterpretations [14]. Incorrect angulation may make a canal appear underfilled or overfilled when it is actually well-obturated.

Advancements in imaging technologies, such as AI-assisted analysis, offer potential solutions to these challenges. AI-driven diagnostic tools can help standardize evaluations by analyzing radiographs with high precision, reducing human error, and increasing the reliability of assessments.

IV. Artificial Intelligence in Dental Imaging

The rapid evolution of AI has significantly transformed dental radiographic imaging by enabling automated detection, classification, and segmentation of complex dental structures. Deep learning (DL) models, particularly convolutional neural networks (CNNs)—have improved diagnostic accuracy by reducing the subjectivity inherent in manual interpretation, and by efficiently analyzing large datasets to detect conditions such as caries, periodontal bone loss, and endodontic anomalies [19]. DL-based algorithmic models excel in tasks ranging from image classification and object detection to segmentation, thereby facilitating the automatic diagnosis of oral lesions and anatomical structures [20]. This shift from traditional, labor-intensive evaluation methods to AI-driven solutions streamlines clinical workflows and supports more objective and reproducible assessments. In this section, we review key AI applications in dental imaging, highlighting how enhanced image quality, robust object detection, and precise segmentation techniques are paving the way for improved treatment planning and overall patient care.

A. AI-Driven Detection and Diagnosis

1) Caries and Lesion Detection: One of the most promising applications of AI in dentistry is the detection of caries and associated lesions, where DL models have demonstrated remarkable diagnostic performance. For instance, a CNN-based approach has been reported to achieve over 80% accuracy in identifying caries on periapical radiographs, outperforming conventional diagnostic methods [21]. Additionally, another DL model applied to bitewing radiographs significantly increased clinicians' sensitivity in detecting early-stage lesions, thereby enhancing preventive interventions [22]. Beyond improving sensitivity, deep neural networks can also identify varying lesion depths with robust specificity, even surpassing experienced practitioners' performance [23]. These findings underscore the value of AI-driven tools in enabling timely and precise caries detection, particularly for subtle lesions that might be overlooked during manual evaluation.

2) Periodontal and Bone Loss Assessment: AI-driven approaches for evaluating periodontal health are now demonstrating clinically significant performance across various radiographic datasets. For example, one study trained a seven-layer CNN to detect periodontal bone loss (PBL) on panoramic radiographs, achieving 0.81 classification accuracy—comparable to that of experienced clinicians [24]. Another investigation employed an ensemble of deep-learning models, including YOLOv5, VGG-16, and U-Net, to identify tooth positions and measure radiographic bone loss on periapical radiographs, reporting overall detection accuracies exceeding 90% [25]. A third study introduced a hybrid framework combining CNN-based methods with conventional computer-aided diagnostic (CAD) processes, showing close agreement with expert diagnoses, evidenced by a correlation coefficient of 0.73 [26].

B. Instance Segmentation and Tooth Identification

1) Tooth Numbering and Classification: A recent study by Budagam et al. [27] introduced an efficient pipeline integrating two deep learning models, YOLOv8 and U-Net, for simultaneous tooth classification and segmentation on panoramic X-ray images. Their novel architecture, referred to as BB-UNet, leverages bounding-box detection from YOLOv8 in conjunction with the segmentation strengths of U-Net, and demonstrated a 3% improvement in mean average precision (mAP) for classification compared to existing methods.

2) Restoration and Anomaly Detection: A recent study explored a self-supervised learning approach (SimMIM and UM-MAE) for detecting dental restorations and segmenting teeth in panoramic radiographs [28]. By leveraging the Swin Transformer architecture, the authors achieved 90.4% and 88.9% performance in detecting teeth and dental restorations, respectively, surpassing a random initialization baseline by more than 12% in average precision. Notably, the method utilized a limited dataset, which was expanded and corrected to enhance the model's generalizability. This research highlights the potential of self-supervised strategies to overcome data scarcity and improve various detection and segmentation tasks in digital dentistry.

C. AI-Enhanced Image Quality and Reconstruction

1) Image Enhancement Systems: A novel network-based approach for dental image enhancement, termed Ded-Net, was recently introduced to address the common issues of non-uniform brightness and low contrast in radiographic imaging [29]. This system decomposes input images into reflection and illumination layers through a multilayer architecture (De-Net) and applies adaptive corrections in an Edification network (Ed-Net). The proposed method not only preserves edges and boundaries but also improves visibility and contrast, making it suitable for early detection of dental diseases and integration into intelligent diagnostic systems. Unlike traditional enhancement algorithms limited by specific conditions, this approach can handle diverse lighting scenarios with a smaller dataset, showing promising adaptability for future clinical applications.

2) 3D Reconstruction and Robotics: Further advancements in AI-driven techniques include a vision-guided robotic system designed to enhance the precision of dental implant surgery [30]. By combining a preoperative cone beam computed tomography (CBCT) scan with real-time visual feedback from a robot-mounted camera, the system accurately registers the patient's oral cavity in the robotic workspace. Force-feedback control also helps modulate pressure during drilling, reducing the likelihood of intraoperative bone damage. Preliminary tests on printed mandible models and subsequent trials on identical molds demonstrated notable improvements in implant placement accuracy compared to traditional manual methods.

V. AI-Based RCT Quality Assessment

The quality assessment of root canal therapy (RCT) has traditionally relied on clinician-based interpretations of radiographs, a process prone to subjective bias and diagnostic inconsistencies. In response, researchers have begun using deep learning algorithms to automate and standardize evaluations of key treatment criteria such as filling length and presence of voids. For instance, one study introduced an anatomy-guided multi-branch Transformer (AGMB-Transformer) network to identify essential landmarks on X-ray images and evaluate RCT outcomes, reporting a final diagnostic accuracy of approximately 90% [31]. This highlights how carefully designed Transformer-based methods could reduce observer variability and offer more consistent feedback for follow-up decisions. In a separate effort, a two-step pipeline combined CenterNet for tooth detection with U-Net for segmenting root canal fillings, demonstrating an approximate 83% agreement with professional endodontists and reinforcing the reliability of such models even under challenging clinical conditions [32].

Still, discrepancies arise when different evaluators or algorithms assess the same radiographic data. One study tested periapical and panoramic images with endodontists, radiologists, and a model named Thakaamed Detect, finding that the AI system tended to assign lower quality scores than the human observers [11]. Such differences underscore the importance of calibrating computational tools to align with established clinical benchmarks. Another investigation evaluated five convolutional neural network (CNN) architectures for segmenting root canal fillings and measuring their proximity to the tooth's apex, with the top model reaching nearly 90% accuracy in distinguishing between overfilled, underfilled, or properly filled canals [33]. Although these studies offer a substantial overview, there remains room for improvement. Key quality parameters like separated instruments, pulpal floor integrity, and periapical health are not fully addressed, and the challenge of evaluating multirooted teeth—especially when some roots overlap in radiographs—remains largely unexplored.

VI. Data Collection and Annotation for AI Training

A. Data Quality and Imaging Standards

The quality of datasets used for training AI models in medical imaging is a crucial factor in ensuring accurate and reliable diagnostic outcomes. High-quality datasets should be large, diverse, and well-annotated to enhance generalizability across different clinical settings [34]. However, many publicly available datasets suffer from limited sample size, inconsistent labeling, and lack of standardized acquisition protocols, leading to potential biases in AI model training. Data-sharing initiatives and open-access repositories have been recognized as essential for advancing AI research in radiology [35]. Despite these efforts, challenges remain regarding data anonymization, privacy concerns, and compliance with regulatory frameworks such as HIPAA and GDPR, which limit accessibility to large-scale dental radiographic datasets [35]. Addressing these limitations requires collaborative data-sharing efforts, rigorous annotation guidelines, and standardized imaging protocols to ensure that AI-driven models can accurately assess root canal treatment quality [34].

Beyond dataset volume and diversity, image quality plays a pivotal role in diagnostic accuracy, particularly in digital intraoral radiographs. Exposure settings, spatial resolution, and contrast optimization significantly impact the visibility of critical endodontic structures such as the root canal filling and periapical tissues [36]. A study optimizing radiographic exposure settings found that contrast perceptibility and spatial resolution improvements led to more precise identification of the endodontic file position relative to the apex, directly influencing clinical decision-making [36]. Additionally, research comparing different digital radiographic systems demonstrated that charge-coupled device (CCD) sensors produce higher-quality images at lower radiation doses, while storage phosphor systems offer more flexibility in exposure settings [37]. Another study evaluating a radiographic checklist intervention highlighted that structured quality control measures may improve radiographic exposure quality but did not significantly impact diagnostic accuracy [38]. Collectively, these studies emphasize that both dataset integrity and image acquisition quality must be optimized to improve AI-driven root canal treatment assessment.

B. Data Sources and Ethical Considerations

The availability of high-quality dental radiographic datasets is fundamental for training AI models in root canal treatment assessment. Various sources contribute to the development of such datasets, including hospital archives, research collaborations, and publicly available datasets. Some of the most notable collections include the Tufts Dental Database, which provides 1,000 expert-annotated panoramic X-ray images for benchmarking AI-based diagnostic systems [39], and a multimodal dental dataset designed to facilitate object detection research with six major dental disease classes [40]. Additionally, a dataset focusing on apical periodontitis lesions in panoramic radiographs was curated from over 16,500 radiographs, enabling the development of deep learning models for periapical lesion detection [41]. Another multimodal dataset includes diverse dental imaging modalities such as CT, panoramic, and periapical radiographs, addressing the need for comprehensive AI training data [42]. Despite these advancements, a critical gap remains: there is currently no widely available dataset specifically designed for root canal treatment quality assessment. The absence of standardized, high-resolution periapical radiographic datasets tailored to root canal-treated teeth limits the development of AI models capable of accurately evaluating root canal filling length, voids, and lateral seal quality.

Beyond dataset availability, ethical considerations play a crucial role in dental AI research. Patient privacy remains a significant challenge, as medical imaging data must comply with strict regulations such as HIPAA and GDPR to ensure confidentiality [35]. Proper anonymization is essential before publicly sharing datasets, yet traditional de-identification methods, such as masking patient identifiers, may not fully protect biometric data. Recent AI-driven anonymization techniques aim to obfuscate biometric traces while preserving image diagnostic quality, ensuring data utility while minimizing re-identification risks [43], [44]. Furthermore, a structured ethical framework is necessary to guide AI adoption in dentistry. One study established a comprehensive checklist covering transparency, privacy protection, accountability, and governance, which stakeholders should consider when developing or deploying AI applications in clinical settings [45]. Ethical concerns extend beyond privacy, encompassing issues like bias in training datasets, potential misdiagnosis due to AI errors, and equitable access to AI-powered diagnostic tools. Addressing these concerns requires stringent data-sharing policies, cross-institutional collaboration, and adherence to standardized ethical guidelines to ensure AI benefits dental diagnostics while upholding patient rights and safety.

C. Annotation and Labeling

Root canal treatment assessment involves evaluating various quality parameters, such as length of root filling, voids, integrity of the lateral seal, irregularities, separated instruments, missed canals, pulpal floor damage and periapical health. A common approach is to use a classifier that assigns cases to predefined categories, such as overfilled, underfilled, or properly filled root fillings. However, this method struggles with data scarcity and distribution challenges, making it difficult to develop a reliable model. Instead, a segmentation-based approach is preferred, where regions of interest (ROIs) are annotated to provide pixel-wise supervision for deep learning models [32], [33]. By segmenting relevant structures, we can leverage domain knowledge along with mathematical and geometrical calculations to estimate quality parameters. Although segmentation is more complex, it enables precise measurements and provides a quantifiable assessment of root canal treatment quality.

A recent study [33] addressed root filling length annotation by employing polygon-based segmentation for the filling material. However, instead of automating apex detection, the study required manual marking of the apex for each prediction, adding an extra step that is time-consuming and prone to inconsistency. To streamline this process, some studies have explored automated apex detection. For instance, YOLO-v9 has been applied to periapical radiographs for apex localization [46]. In this method, apexes were detected using rectangular bounding boxes, with the midpoint taken as the apex. While effective, this approach may introduce positional errors depending on bounding box placement. An alternative, more precise method is keypoint detection, where models like Keypoint R-CNN directly predict the coordinates of root apexes [47]. This avoids the need for bounding box approximations and enhances accuracy in apex localization. Given the comparable accuracy of both approaches, researchers can choose between bounding box-based detection (YOLO-v9) and keypoint-based detection (Keypoint R-CNN) based on dataset availability and annotation preferences.

D. Dataset Preprocessing

Preprocessing is a crucial step in preparing dental radiographs for AI-based root canal treatment evaluation. The goal is to enhance the visibility of key anatomical structures while mitigating issues such as noise, low contrast, and artifacts that can hinder accurate segmentation and classification. Various preprocessing techniques are applied to optimize radiographic images, ensuring that AI models can effectively learn from high-quality inputs.

One of the most commonly used techniques in radiographic image enhancement is Contrast-Limited Adaptive Histogram

Equalization (CLAHE), which improves local contrast without over-amplifying noise. Studies have demonstrated that CLAHE significantly enhances the visibility of periapical structures, making it easier to detect the root apex and assess filling quality [48]. Compared to traditional Histogram Equalization (HE), CLAHE produces more uniform brightness distribution while preserving details, making it more suitable for dental radiographs [48], [49]. However, some studies suggest that HE can still be useful in certain cases where global contrast improvement is required [48]. Other contrast enhancement methods, such as Contourlet Transform (CT), Wavelet Transform, and Contrast Stretching (CS), have also been explored, with CT yielding the highest Peak Signal-to-Noise Ratio (PSNR), indicating superior enhancement performance [49].

Beyond contrast enhancement, noise reduction is another essential preprocessing step. Radiographs taken with low radiation doses often exhibit grainy textures and random noise, which can obscure fine details. Multi-scale Mathematical Morphology (MSTHGR), a technique based on geodesic reconstruction, has been shown to effectively suppress noise while preserving edge details in panoramic dental radiographs [50]. This method outperforms traditional noise-reduction techniques such as Gamma Correction (GC), Bi-Histogram Equalization (BBHE), and Dual Sub-Image Histogram Equalization (DSIHE) in terms of contrast improvement and spatial frequency preservation [50]. The application of Top-Hat Transform and Marker-Based Image Reconstruction further refines the contrast enhancement process, helping to highlight critical endodontic structures [50].

Additionally, edge enhancement techniques are applied to sharpen the boundaries of root canals and periapical tissues. Adaptive histogram equalization variants, such as Median Adaptive Histogram Equalization (MAHE) and Sharp Contrast Adaptive Histogram Equalization (SCLAHE), have been tested for dental X-ray interpretation [51]. These techniques improve diagnostic ability, particularly for detecting periapical pathologies, by increasing the clarity of bone and soft tissue structures [51].

VII. Traditional Image Processing for RCT Evaluation

Traditional image processing techniques played a significant role in the evaluation of root canal treatment, contributing to assessments of canal morphology, the effects of instrumentation, and overall treatment outcomes. Early methods relied on direct visualization, where teeth were sectioned to observe root canals, and model creation, where dyes or resins were injected to create three-dimensional representations [52] [53]. Radiography was also employed, utilizing radiopaque materials to provide two-dimensional images of the root canal. However, these traditional methods had limitations, such as evaluating canals only before or after preparation and the inability of model materials to accurately replicate dentin properties.

Digital Subtraction Radiography (DSR) emerged as a significant advancement, enabling visualization of changes by subtracting postoperative radiographs from preoperative ones and using contrast enhancement to highlight differences [52]. This technique facilitated the visualization of dentin loss during instrumentation and simultaneous comparison of canal morphology before and after treatment. Quantitative evaluation of canal enlargement was achieved through region segmentation and area measurement processes.

Direct digital radiography (DDR) brought further improvements, including reduced radiation dosage, elimination of chemical waste, and instant imaging with enhancement capabilities [54]. DDR systems enabled on-screen point-to-point measurements, improving the precision of assessments (fig. 5). Studies comparing DDR with conventional radiography for determining endodontic file length yielded varied results, with some showing comparable accuracy, and others indicating potential underestimation with DDR, particularly in curved canals [54]. As DDR technology advanced, image quality improved, making it comparable to conventional radiographs for estimating canal lengths, even in complex canal anatomies.

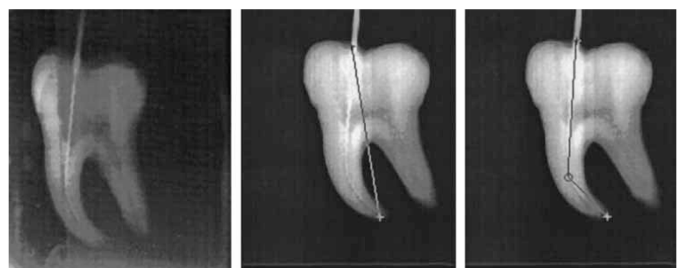

Fig. 5. Examples of the radiographic image, the screenshot of the DDR image with 2 clicks and 3 clicks of a tooth.

Image processing algorithms became essential for enhancing image characteristics [55] [56]. These algorithms, designed to correct for exponential attenuation of X-rays and adjust for the human visual system's response, aimed to represent equal steps in object thickness as equal steps in brightness on computer monitors [52] [55]. Techniques such as contrast enhancement, edge enhancement, and brightness/contrast adjustments were commonly used to improve the detection of thin file tips, requiring careful optimization to balance contrast and detail [56].

Specific digital techniques offered unique advantages:

- **Digital Subtraction Radiography (DSR)**: Enabled visualization of dentin loss areas and quantitative evaluation of root canal enlargement.
- **Automatic Segmentation**: Facilitated automatic segmentation of root canal areas on radiographic images, allowing for precise measurements of enlargement before and after instrumentation.
- **Micro-computed Tomography (MCT)**: Provided advanced 3D visualization and study of root canal morphology, enabling quantitative study and geometrical measurements of changes in root canal volumes and surface areas.

However, it required costly hardware/software and skilled personnel [52] [54].

- **Photostimulable Storage Phosphor Luminescence (PSPL) Imaging**: Offered image definition equivalent to E-speed film for measuring clinical root lengths and file lengths, with the benefit of contrast variability, image enhancement and magnification. Digital imaging showed some indication of being more accurate for assessing file length [57].

Techniques like Contrast Limited Adaptive Histogram Equalization (CLAHE) are commonly used for contrast enhancement [48], but they do not always yield desirable results on intraoral periapical (IOPA) images. In some cases, CLAHE can enhance unwanted features by increasing the intensity of normal tooth areas when attempting to detect root fillings. However, when applied to root canal detection, CLAHE proves beneficial by highlighting critical structures and improving the visibility of the canal morphology.

In addition, digital image analysis methods have been employed to localize the periapical region in dental radiographs. An algorithm designed to obtain information on the orientation of roots mathematically approximates a curve using a cubic polynomial to intersect the boundary of the root at its apex [58]. This approach demonstrated promising potential for aiding digital analysis of the periapical region, contributing to more accurate diagnosis and evaluation of root canal treatments.

Image post-processing, a key aspect of digital radiography, enhanced image quality and interpretation accuracy through various functions, including image restoration, enhancement, analysis, synthesis, and compression [56]. Despite these advancements, digital systems were sometimes inferior to film when using smaller file sizes, and factors like image noise and enhancement algorithms could affect the visibility of fine details [59].

In conclusion, while digital systems offer numerous advantages such as enhanced visualization and quantitative analysis, it was crucial to carefully consider image quality, file size, and the application of appropriate enhancement techniques to ensure accurate assessment of root canal treatments [60]. The ongoing development and refinement of these techniques continuously improved the precision and effectiveness of endodontic practices.

VIII. Machine Learning Techniques for RCT Evaluation

Several deep learning (DL) and machine learning (ML) techniques have been utilized and evaluated in the context of root canal treatment (RCT), focusing on diverse aspects such as feature detection, classification, prognosis, and treatment outcome. The choice of these techniques is justified by their capacity to automate processes, improve diagnostic accuracy, and predict treatment outcomes, thus enhancing clinical decision-making and patient care [61] [62].

Convolutional Neural Networks (CNNs) are extensively applied for image-based automated diagnosis in dentistry. CNNs are favored for their ability to automatically classify datasets and deeply learn features contained within the data through multi-layer architectures [63] [64]. Their architecture allows them to exploit local connections, shared weights, and pooling, making them particularly suitable for imaging diagnosis [65].

- **Faster R-CNN**: A CNN architecture used for teeth detection and numbering in dental periapical films (fig. 6). It evolves from R-CNN and Fast R-CNN, using a region proposal network to improve object detection speed and accuracy [65] [63].

- **PRESSAN-17**: A 17-layer deep CNN (DCNN) [66] with a self-attention layer and residual blocks, developed to detect clinical features on periapical radiographs. This model can detect features such as full coverage restoration, coronal defects, previous root fillings, and canal visibility. PRESSAN-17 predicts the three-year endodontic prognosis by analyzing preoperative periapical radiographs. The inclusion of a self-attention layer allows the model to capture long-range dependencies across image regions.
- **YOLO Versions**: The YOLO (You Only Look Once) family of models has seen multiple iterations applied in dental imaging. YOLO version 3 was trained to score periapical lesions on intraoral periapical radiographs (IOPAR) based on the periapical index (PAI) scoring system [67]. YOLOv8, the latest version, was employed for instance segmentation and teeth classification in panoramic X-rays, featuring architectural enhancements like CSPDarknet53 and anchor-free detection for improved accuracy and speed [27]. Moreover, YOLOv9 has been utilized to automate bone loss measurement on periapical radiographs, aiding in the prediction of periodontitis stage and grade with high accuracy and reliability [46].
- **Gabor Filtered-CNN**: A model that exhibited high accuracy in detecting separated endodontic instruments (SEI) on dental radiographs [68]. The Gabor filter enhances the image for machine learning, improving the detection of the instrument's pixel.
- **Mask R-CNN**: A segmentation algorithm designed to outline the root in preoperative periapical radiographic images with known treatment results to predict class labels for healed, healing, and diseased teeth [63].Additionally, R-CNN models have been effectively applied for assessing radiographic bone loss in the posterior maxilla, utilizing Mask R-CNN with a ResNet50-FPN backbone for precise feature extraction and keypoint detection [47]
- **U-Net**: A fully convolutional neural network (fig. 7) widely used for medical image segmentation, including root canal treatment images [32]. The U-Net architecture features a U-shaped structure with a contracting path to capture context and a symmetric expanding path for precise localization. In root canal therapy evaluation, U-Net segments the root canal filling area and corresponding

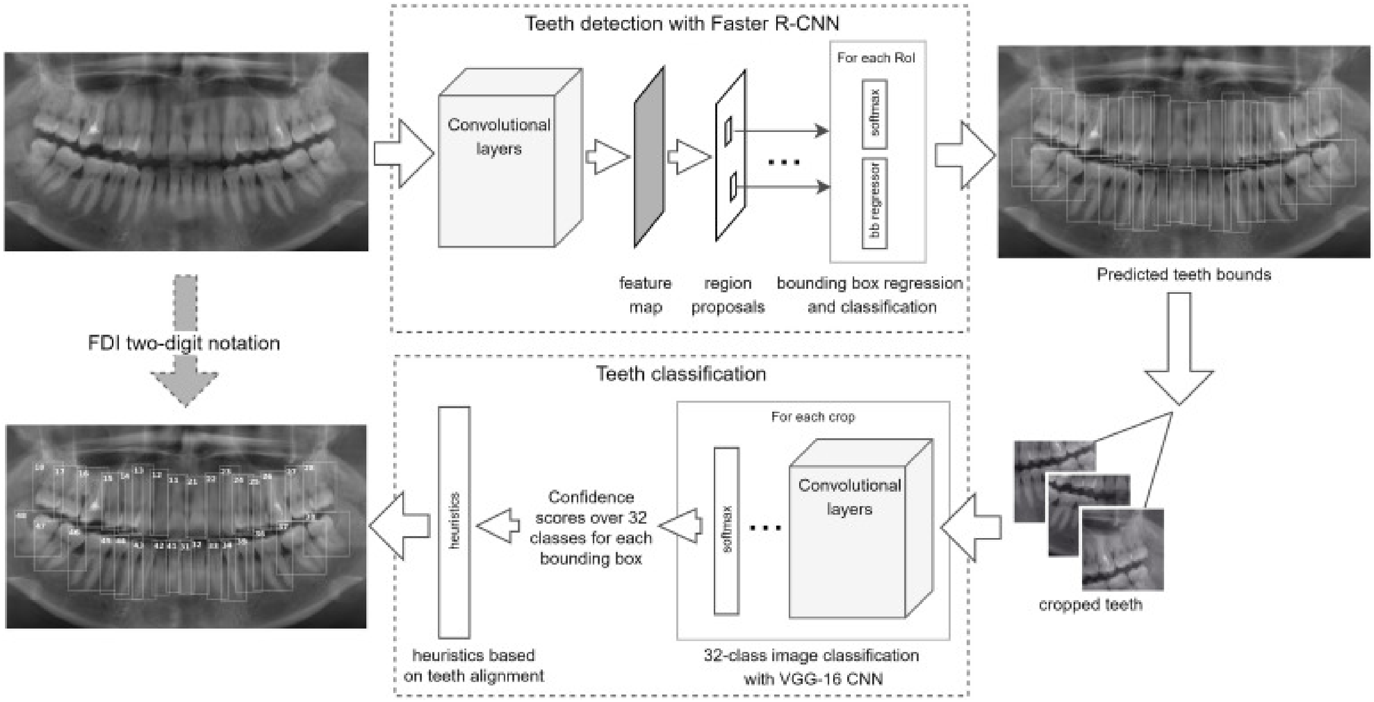

Fig. 6. Teeth detection and teeth classification with CNN.

tooth area, contributing to accurate quality assessments.

- **CenterNet**: A keypoint-based object detection model utilized to detect root canal targets in dental images [32]. CenterNet describes objects using their center points, improving detection accuracy by avoiding anchor box designs. In the context of root canal therapy, CenterNet is used to localize treated teeth within radiographs, enhancing the subsequent segmentation and evaluation process.

Long Short-Term Memory (LSTM) networks, typically used for processing sequential data, were also explored in the context of endodontics. Although LSTMs are known for their strength in capturing long-range dependencies, studies have found that CNN models, particularly Gabor filtered-CNN, perform better in detecting separated endodontic instruments. To use the LSTM model with image data, a windowed feature extraction mechanism was introduced to extract features along a line suspected to be SEI at each sliding window. This approach aimed to reduce sensitivity to variations in orientation and size. In a study, at least 775 samples were needed to detect a 5% accuracy benefit when applying the CNN models compared to LSTM models [68].

Deep Neural Networks (DNNs), derived from artificial neural networks (ANN), have been utilized for general data classification and to predict the likelihood of root fracture following root canal treatment and crown placement. DNNs consist of input, hidden, and output layers, allowing them to model complex patterns in data. For instance, a study predicting root fractures used a DNN with three hidden layers, each containing 425 nodes, which was determined experimentally to provide the best classification ability [69]. The use of all available features improves the accuracy of the prediction.

Various Machine Learning Models are also used for various purposes.

- **Support Vector Machines (SVM)**: Employed to categorize failed RCT cases into distinct classes and predict treatment longevity [70]. SVM is effective in high-dimensional spaces and can handle non-linear data through the use of kernel functions.
- **Logistic Regression (LR)**: Another technique used to identify factors causing root canal treatment failure [70]. LR is favored for its simplicity and efficiency in binary classification problems, providing probabilities of outcomes. In one study, logistic regression had a higher level of accuracy (92.47%) compared to other methods.
- **Gradient Boosting Machine (GBM)** and **Random Forest (RF)**: Applied for prognosis prediction in endodontic microsurgery [71]. GBM and RF are capable of handling large datasets and complex non-linear relationships, identifying important predictors for treatment outcomes. In one study, the GBM model slightly outperformed the RF model [61]. The XGBoost model had the lowest error values and highest explained variance, making it useful in preoperative analysis.

Additionally, deep learning models have been developed to assist in Periapical Index (PAI) Scoring, which involves categorizing periapical lesions. Automated PAI scoring reduces human bias and improves the consistency of diagnosis. The CNN model can be trained to perform multiple classifications by providing detailed annotations of all possible subclasses of the periapical lesion.

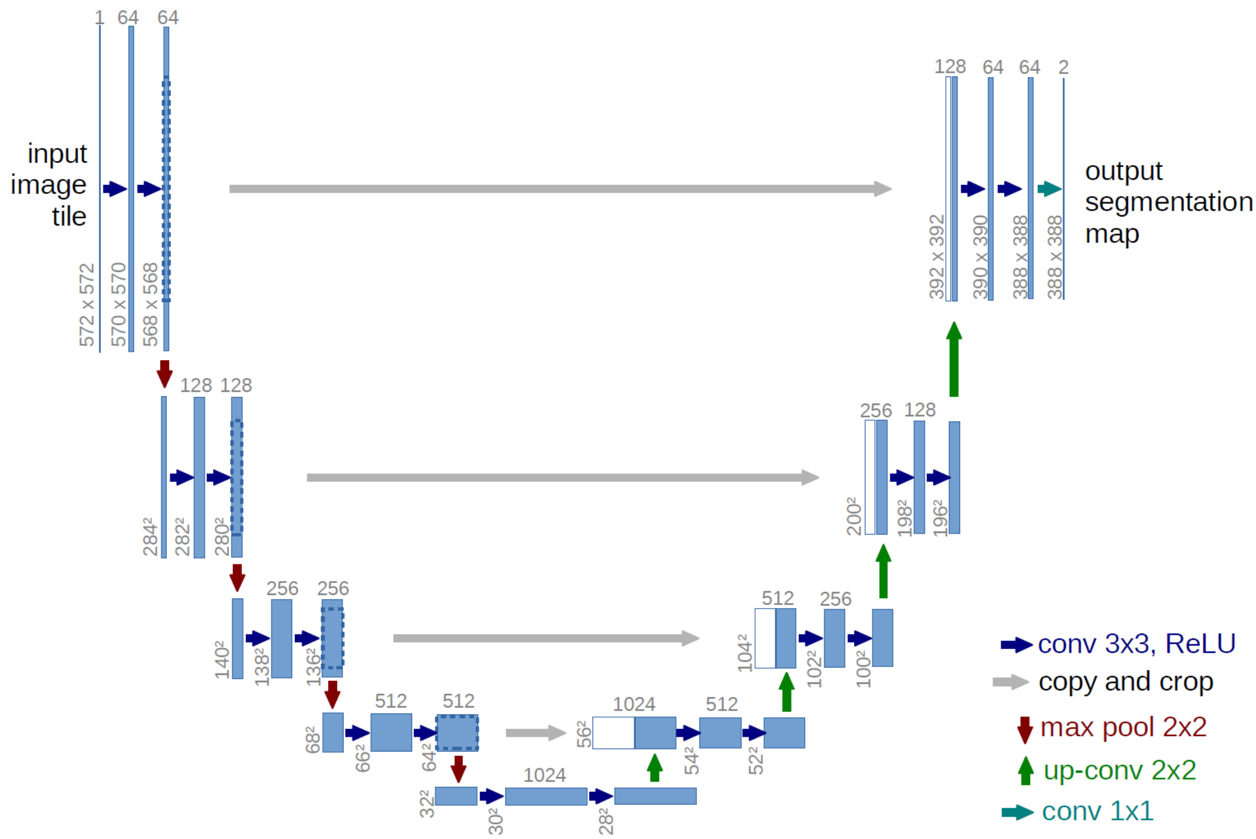

Fig. 7. U-net network structure

In a systematic review of AI applications in dental and maxillofacial radiology (DMFR), it was noted that AI models are being developed for a range of clinical issues, including the localization of cephalometric landmarks, diagnosis of osteoporosis, classification/segmentation of maxillofacial cysts and tumors, and identification of periodontitis/peri-apical disease [62]. The performance of these models varies depending on the algorithms used, and it is essential to verify their generalizability and reliability using representative images. The use of both 2D and 3D imaging modalities is common, with CBCT images increasingly used to develop AI models for various clinical applications.

IX. Conclusion

The current landscape of artificial intelligence applications in the quality assessment of final root canal treatment using dental radiographs was examined in this review. The limitations of traditional manual evaluation methods, including subjectivity, variability among clinicians, and challenges associated with radiographic image quality, were highlighted. It was shown that these issues can be addressed by artificial intelligence approaches that provide more objective, standardized, and precise assessments.

Various deep learning architectures such as convolutional neural networks, U-Net, and keypoint detection models were described. Their potential in automating tasks such as root canal filling segmentation and apex localization was demonstrated. The evolution of traditional image processing techniques toward more advanced methods using artificial intelligence was discussed, and key challenges in data collection, annotation, and ethical considerations were examined. Overcoming these challenges is considered necessary for further integration of these technologies into clinical practice.

Continued advancements in artificial intelligence and machine learning, along with improvements in data sharing and standardized imaging protocols, are expected to enhance the reliability and efficiency of root canal treatment evaluations. Early detection of treatment deficiencies is anticipated, and support is expected to be provided to clinicians in making more informed decisions, ultimately leading to improved patient outcomes.

References

[1] G. Bardini, L. Casula, E. Ambu, D. Musu, M. Mercadè, and E. Cotti, "A 12-month follow-up of primary and secondary root canal treatment in teeth obturated with a hydraulic sealer," *Clinical Oral Investigations*, vol. 25, pp. 2757–2764, 2021.

[2] K. Gulabivala and Y. L. Ng, "Factors that affect the outcomes of root canal treatment and retreatment—a reframing of the principles," *International Endodontic Journal*, vol. 56, pp. 82–115, 2023.

[3] G. S. Cheung, "Survival of first-time nonsurgical root canal treatment performed in a dental teaching hospital," *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology, and Endodontology*, vol. 93, no. 5, pp. 596–604, 2002.

[4] N. Al-Nuaimi, S. Patel, A. Davies, A. Bakhsh, F. Foschi, and F. Mannocci, "Pooled analysis of 1-year recall data from three root canal treatment outcome studies undertaken using cone beam computed tomography," *International Endodontic Journal*, vol. 51, pp. e216–e226, 2018.

[5] J. Peak, S. Hayes, S. Bryant, and P. Dummer, "The outcome of root canal treatment. a retrospective study within the armed forces (royal air force)," *British dental journal*, vol. 190, no. 3, pp. 140–144, 2001.

[6] S. E. Hoskinson, Y.-L. Ng, A. E. Hoskinson, D. R. Moles, and K. Gulabivala, "A retrospective comparison of outcome of root canal treatment using two different protocols," *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology, and Endodontology*, vol. 93, no. 6, pp. 705–715, 2002.

[7] Y.-L. Ng, V. Mann, S. Rahbaran, J. Lewsey, and K. Gulabivala, "Outcome of primary root canal treatment: systematic review of the literature–part 2. influence of clinical factors," *International endodontic journal*, vol. 41, no. 1, pp. 6–31, 2008.

[8] J. P. Van Nieuwenhuysen, W. D'Hoore, and J. G. Leprince, "What ultimately matters in root canal treatment success and tooth preservation: A 25-year cohort study," *International Endodontic Journal*, vol. 56, no. 5, pp. 544–557, 2023.

[9] C. Estrela, R. Holland, C. R. d. A. Estrela, A. H. G. Alencar, M. D. Sousa-Neto, and J. D. Pécora, "Characterization of successful root canal treatment," *Brazilian dental journal*, vol. 25, no. 1, pp. 3–11, 2014.

[10] S. Eliyas, P. Briggs, I. Harris, J. Newton, and J. Gallagher, "Development of quality measurement instruments for root canal treatment," *International endodontic journal*, vol. 50, no. 7, pp. 652–666, 2017.

[11] S. M. Sobhy and S. F. Ahmed, "Investigating the variability in root canal filling quality evaluations among endodontist, radiologist and artificial intelligence in periapical and panoramic radiographs." *Egyptian Dental Journal*, vol. 70, no. 4, pp. 3869–3877, 2024.

[12] A. Halse and O. Molven, "Overextended gutta-percha and kloroperka n-ö root canal fillings: Radiographic findings after 10-17 years," *Acta Odontologica Scandinavica*, vol. 45, no. 3, pp. 171–177, 1987.

[13] A. A. Habib, M. D. Doumani, M. Z. Nassani, E. Shamsy, B. S. Jto, H. A. Arwadi, and S. A. Mohamed, "Radiographic assessment of the quality of root canal fillings performed by senior dental students," *Eur Endod J*, vol. 3, no. 2, pp. 101–6, 2018.

[14] Z. Mohammadi, S. Asgary, S. Shalavi, and P. V. Abbott, "A clinical update on the different methods to decrease the occurrence of missed root canals," *Iranian endodontic journal*, vol. 11, no. 3, p. 208, 2016.

[15] F. Costa, J. Pacheco-Yanes, J. Siqueira Jr, A. Oliveira, I. Gazzaneo, C. Amorim, P. Santos, and F. Alves, "Association between missed canals and apical periodontitis," *International endodontic journal*, vol. 52, no. 4, pp. 400–406, 2019.

[16] K. Nasiri and K.-T. Wrbas, "Management of separated instruments in root canal therapy," *Journal of Dental Sciences*, vol. 18, no. 3, p. 1433, 2023.

[17] E. S. of Endodontology, "Quality guidelines for endodontic treatment: consensus report of the european society of endodontology," *International endodontic journal*, vol. 39, no. 12, pp. 921–930, 2006.

[18] A. A. Habib, M. I. Taha, and E. M. Farah, "Methodologies used in quality assessment of root canal preparation techniques: Review of the literature," *Journal of Taibah University Medical Sciences*, vol. 10, no. 2, pp. 123–131, 2015.

[19] H. Ding, J. Wu, W. Zhao, J. P. Matinlinna, M. F. Burrow, and J. K. Tsoi, "Artificial intelligence in dentistry—a review," *Frontiers in Dental Medicine*, vol. 4, p. 1085251, 2023.

[20] H. Kim, "Deep learning in dental radiographic imaging," *Journal of the Korean Academy of Pediatric Dentistry*, vol. 51, no. 1, pp. 1–10, 2024.

[21] J.-H. Lee, D.-H. Kim, S.-N. Jeong, and S.-H. Choi, "Detection and diagnosis of dental caries using a deep learning-based convolutional neural network algorithm," *Journal of dentistry*, vol. 77, pp. 106–111, 2018.

[22] S. Lee, S.-i. Oh, J. Jo, S. Kang, Y. Shin, and J.-w. Park, "Deep learning for early dental caries detection in bitewing radiographs," *Scientific reports*, vol. 11, no. 1, p. 16807, 2021.

[23] A. G. Cantu, S. Gehrung, J. Krois, A. Chaurasia, J. G. Rossi, R. Gaudin, K. Elhennawy, and F. Schwendicke, "Detecting caries lesions of different radiographic extension on bitewings using deep learning," *Journal of dentistry*, vol. 100, p. 103425, 2020.

[24] J. Krois, T. Ekert, L. Meinhold, T. Golla, B. Kharbot, A. Wittemeier, C. Dörfer, and F. Schwendicke, "Deep learning for the radiographic detection of periodontal bone loss," *Scientific reports*, vol. 9, no. 1, p. 8495, 2019.

[25] C.-C. Chen, Y.-F. Wu, L. M. Aung, J. C.-Y. Lin, S. T. Ngo, J.-N. Su, Y.-M. Lin, and W.-J. Chang, "Automatic recognition of teeth and periodontal bone loss measurement in digital radiographs using deep-learning artificial intelligence," *Journal of Dental Sciences*, vol. 18, no. 3, pp. 1301–1309, 2023.

[26] H.-J. Chang, S.-J. Lee, T.-H. Yong, N.-Y. Shin, B.-G. Jang, J.-E. Kim, K.-H. Huh, S.-S. Lee, M.-S. Heo, S.-C. Choi *et al.*, "Deep learning hybrid method to automatically diagnose periodontal bone loss and stage periodontitis," *Scientific reports*, vol. 10, no. 1, p. 7531, 2020.

[27] D. Budagam, A. Kumar, S. Ghosh, A. Shrivastav, A. Z. Imanbayev, I. R. Akhmetov, D. Kaplun, S. Antonov, A. Rychenkov, G. Cyganov *et al.*, "Instance segmentation and teeth classification in panoramic x-rays," *arXiv preprint arXiv:2406.03747*, 2024.

[28] A. Almalki and L. J. Latecki, "Self-supervised learning with masked image modeling for teeth numbering, detection of dental restorations, and instance segmentation in dental panoramic radiographs," in *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, 2023, pp. 5594–5603.

[29] R. Khan, S. Akbar, A. Khan, M. Marwan, Z. H. Qaisar, A. Mehmood, F. Shahid, K. Munir, and Z. Zheng, "Dental image enhancement network for early diagnosis of oral dental disease," *Scientific Reports*, vol. 13, no. 1, p. 5312, 2023.

[30] D. Pisla, V. Bulbucan, M. Hedesiu, C. Vaida, I. Zima, R. Mocan, P. Tucan, C. Dinu, D. Pisla, and T. P. Group, "A vision-guided robotic system for safe dental implant surgery," *Journal of Clinical Medicine*, vol. 13, no. 21, p. 6326, 2024.

[31] Y. Li, G. Zeng, Y. Zhang, J. Wang, Q. Jin, L. Sun, Q. Zhang, Q. Lian, G. Qian, N. Xia *et al.*, "Agmb-transformer: Anatomy-guided multi-branch transformer network for automated evaluation of root canal therapy," *IEEE Journal of Biomedical and Health Informatics*, vol. 26, no. 4, pp. 1684–1695, 2021.

[32] J. Liu, G. Peng, and S. Yan, "An intelligent evaluation method of root canal therapy quality based on deep learning," in *2022 China Automation Congress (CAC)*. IEEE, 2022, pp. 6254–6259.

[33] B. Çelik, M. Z. Genç, and M. E. Çelik, "Evaluation of root canal filling length on periapical radiograph using artificial intelligence," *Oral Radiology*, pp. 1–9, 2024.

[34] L. Pinto-Coelho, "How artificial intelligence is shaping medical imaging technology: A survey of innovations and applications," *Bioengineering*, vol. 10, no. 12, p. 1435, 2023.

[35] L. C. Bell and E. Shimron, "Sharing data is essential for the future of ai in medical imaging," *Radiology: Artificial Intelligence*, vol. 6, no. 1, p. e230337, 2023.

[36] A. B. Barrineau, P. Mah, and S. M. Mallya, "Improvements in image quality after optimization in digital intraoral radiographs," *The Journal of the American Dental Association*, vol. 154, no. 1, pp. 24–31, 2023.

[37] S. M. d. Almeida, A. E. F. d. Oliveira, R. I. Ferreira, and F. N. Bóscolo, "Image quality in digital radiographic systems," *Brazilian dental journal*, vol. 14, pp. 136–171, 2003.

[38] M. W. Nenad, C. Halupa, A. E. Spolarich, and J. R. Gurenlian, "A dental radiography checklist as a tool for quality improvement," *American Dental Hygienists' Association*, vol. 90, no. 6, pp. 386–393, 2016.

[39] K. Panetta, R. Rajendran, A. Ramesh, S. P. Rao, and S. Agaian, "Tufts dental database: a multimodal panoramic x-ray dataset for benchmarking diagnostic systems," *IEEE journal of biomedical and health informatics*, vol. 26, no. 4, pp. 1650–1659, 2021.

[40] R. B. Rahman, S. A. Tanim, N. Alfaz, T. E. Shrestha, M. S. U. Miah, and M. Mridha, "A comprehensive dental dataset of six classes for deep learning based object detection study," *Data in Brief*, vol. 57, p. 110970, 2024.

[41] H. V. Do, T. N. N. Vo, P. T. Nguyen, T. H. L. Luong, N. G. Cu, and H. S. Le, "A dataset of apical periodontitis lesions in panoramic radiographs for deep-learning-based classification and detection," *Data in Brief*, vol. 54, p. 110486, 2024.

[42] Y. Huang, W. Liu, C. Yao, X. Miao, X. Guan, X. Lu, X. Liang, L. Ma, S. Tang, Z. Zhang *et al.*, "A multimodal dental dataset facilitating machine learning research and clinic services," *Scientific Data*, vol. 11, no. 1, p. 1291, 2024.

[43] K. Packhäuser, S. Gündel, F. Thamm, F. Denzinger, and A. Maier, "Deep learning-based anonymization of chest radiographs: a utility-preserving measure for patient privacy," in *International Conference on Medical*

Image Computing and Computer-Assisted Intervention. Springer, 2023, pp. 262–272.

[44] L. Fezai, T. Urruty, P. Bourdon, C. Fernandez-Maloigne, and A. D. N. Initiative, "Deep anonymization of medical imaging," *Multimedia Tools and Applications*, vol. 82, no. 6, pp. 9533–9547, 2023.

[45] R. Rokhshad, M. Ducret, A. Chaurasia, T. Karteva, M. Radenkovic, J. Roganovic, M. Hamdan, H. Mohammad-Rahimi, J. Krois, P. Lahoud *et al.*, "Ethical considerations on artificial intelligence in dentistry: a framework and checklist," *Journal of Dentistry*, vol. 135, p. 104593, 2023.

[46] N. Ameli, M. P. Gibson, I. Kornerup, M. Lagravere, M. Gierl, and H. Lai, "Automating bone loss measurement on periapical radiographs for predicting the periodontitis stage and grade," *Frontiers in Dental Medicine*, vol. 5, p. 1479380, 2024.

[47] A. Vollmer, M. Vollmer, G. Lang, A. Straub, A. Kübler, S. Gubik, R. C. Brands, S. Hartmann, and B. Saravi, "Automated assessment of radiographic bone loss in the posterior maxilla utilizing a multi-object detection artificial intelligence algorithm," *Applied Sciences*, vol. 13, no. 3, p. 1858, 2023.

[48] M. Mehdizadeh, K. Tavakoli Tafti, and P. Soltani, "Evaluation of histogram equalization and contrast limited adaptive histogram equalization effect on image quality and fractal dimensions of digital periapical radiographs," *Oral Radiology*, vol. 39, no. 2, pp. 418–424, 2023.

[49] H. Rahmi-Fajrin, S. Puspita, S. Riyadi, and E. Sofiani, "Dental radiography image enhancement for treatment evaluation through digital image processing," *Journal of clinical and experimental dentistry*, vol. 10, no. 7, p. e629, 2018.

[50] J. C. M. Román, V. R. Fretes, C. G. Adorno, R. G. Silva, J. L. V. Noguera, H. Legal-Ayala, J. D. Mello-Román, R. D. E. Torres, and J. Facon, "Panoramic dental radiography image enhancement using multiscale mathematical morphology," *Sensors*, vol. 21, no. 9, p. 3110, 2021.

[51] S. A. Ahmad, M. N. Taib, N. E. A. Khalid, and H. Taib, "An analysis of image enhancement techniques for dental x-ray image interpretation," *International Journal of Machine Learning and Computing*, vol. 2, no. 3, p. 292, 2012.

[52] G. Mikrogeorgis, I. Molyvdas, K. Lyroudia, N. Nikolaidis, and I. Pitas, "A new methodology for the comparative study of the root canal instrumentation techniques based on digital radiographic image processing and analysis," *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology, and Endodontology*, vol. 101, no. 6, pp. e125–e131, 2006.

[53] D. C. Gullickson and S. Montgomery, "The study of root canal morphology using a digital image processing technique," *Journal of Endodontics*, vol. 13, no. 4, pp. 158–163, 1987.

[54] A. Mentes and N. Gencoglu, "Canal length evaluation of curved canals by direct digital or conventional radiography," *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology, and Endodontology*, vol. 93, no. 1, pp. 88–91, 2002.

[55] G. Li, G. Sanderink, U. Welander, W. McDavid, and K. Nasstrom, "Evaluation of endodontic files in digital radiographs before and after employing three image processing algorithms," *Dentomaxillofacial Radiology*, vol. 33, no. 1, pp. 6–11, 2004.

[56] O. Gormez and H. H. Yilmaz, "Image post-processing in dental practice," *European Journal of Dentistry*, vol. 3, no. 04, pp. 343–347, 2009.

[57] R. A. Cederberg, E. Tidwell, N. L. Frederiksen, and B. W. Benson, "Endodontic working length assessment: Comparison of storage phosphor digital imaging and radiographic film," *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology, and Endodontology*, vol. 85, no. 3, pp. 325–328, 1998.

[58] A. Mol and P. F. van der Stelt, "Locating the periapical region in dental radiographs using digital image analysis," *Oral surgery, oral medicine, oral pathology*, vol. 75, no. 3, pp. 373–382, 1993.

[59] G. C. Sanderink, R. Huiskens, P. Van der Stelt, U. S. Welander, and S. E. Stheeman, "Image quality of direct digital intraoral x-ray sensors in assessing root canal length: the radiovisiography, visualix/vixa, sensa-ray, and flash dent systems compared with ektaspeed films," *Oral surgery, oral medicine, oral pathology*, vol. 78, no. 1, pp. 125–132, 1994.

[60] S. Nikneshan, R. Boroumand, N. Esmaeeli, A. Azadikhah, and M. Paknahad, "The effect of different image processing techniques on the measurement accuracy of endodontics file length," *Journal of Dentistry*, vol. 24, no. 3, p. 335, 2023.

[61] Y. Qu, Y. Wen, M. Chen, K. Guo, X. Huang, and L. Gu, "Predicting case difficulty in endodontic microsurgery using machine learning algorithms," *Journal of Dentistry*, vol. 133, p. 104522, 2023.

[62] K. Hung, C. Montalvao, R. Tanaka, T. Kawai, and M. M. Bornstein, "The use and performance of artificial intelligence applications in dental and maxillofacial radiology: A systematic review," *Dentomaxillofacial Radiology*, vol. 49, no. 1, p. 20190107, 2020.

[63] H. Chen, K. Zhang, P. Lyu, H. Li, L. Zhang, J. Wu, and C.-H. Lee, "A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films," *Scientific reports*, vol. 9, no. 1, p. 3840, 2019.

[64] T. Hiraiwa, Y. Ariji, M. Fukuda, Y. Kise, K. Nakata, A. Katsumata, H. Fujita, and E. Ariji, "A deep-learning artificial intelligence system for assessment of root morphology of the mandibular first molar on panoramic radiography," *Dentomaxillofacial Radiology*, vol. 48, no. 3, p. 20180218, 2019.

[65] D. V. Tuzoff, L. N. Tuzova, M. M. Bornstein, A. S. Krasnov, M. A. Kharchenko, S. I. Nikolenko, M. M. Sveshnikov, and G. B. Bednenko, "Tooth detection and numbering in panoramic radiographs using convolutional neural networks," *Dentomaxillofacial Radiology*, vol. 48, no. 4, p. 20180051, 2019.

[66] J. Lee, H. Seo, Y. J. Choi, C. Lee, S. Kim, Y. S. Lee, S. Lee, and E. Kim, "An endodontic forecasting model based on the analysis of preoperative dental radiographs: a pilot study on an endodontic predictive deep neural network," *Journal of endodontics*, vol. 49, no. 6, pp. 710–719, 2023.

[67] N. P. Moidu, S. Sharma, A. Chawla, V. Kumar, and A. Logani, "Deep learning for categorization of endodontic lesion based on radiographic periapical index scoring system," *Clinical Oral Investigations*, vol. 26, no. 1, pp. 651–658, 2022.

[68] C. Buyuk, B. Arican Alpay, and F. Er, "Detection of the separated root canal instrument on panoramic radiograph: a comparison of lstm and cnn deep learning methods," *Dentomaxillofacial Radiology*, vol. 52, no. 3, p. 20220209, 2023.

[69] W.-T. Chang, H.-Y. Huang, T.-M. Lee, T.-Y. Sung, C.-H. Yang, and Y.-M. Kuo, "Predicting root fracture after root canal treatment and crown installation using deep learning," *Journal of Dental Sciences*, vol. 19, no. 1, pp. 587–593, 2024.

[70] P. Choudhari, A. S. Rajawat, and S. Goyal, "Longevity recommendation for root canal treatment using machine learning," *Engineering Proceedings*, vol. 59, no. 1, p. 193, 2024.

[71] Y. Qu, Z. Lin, Z. Yang, H. Lin, X. Huang, and L. Gu, "Machine learning models for prognosis prediction in endodontic microsurgery," *Journal of Dentistry*, vol. 118, p. 103947, 2022.