Evaluating the Accuracy of Measuring Endodontic Working Length from Diagnostic Radiographs Using Artificial Intelligence: An In Vitro Study.

Abstract:

Successful root canal treatment largely depends on accurate working length determination, as errors in measurement may lead to incomplete cleaning or over-instrumentation of the canal. Conventional techniques such as radiographic assessment and electronic apex locators are widely used, but they may be influenced by operator experience, anatomical variations, and image interpretation errors. With recent advances in artificial intelligence (AI), deep learning models have shown promising applications in dental imaging and automated diagnosis. The present study was conducted to evaluate the accuracy of measuring endodontic working length from diagnostic radiographs using an AI-based approach. Diagnostic radiographs of single-rooted teeth were collected and processed through image enhancement and normalization techniques. A convolutional autoencoder model was used to identify and segment the root canal area, after which skeletonization and contour analysis were performed to calculate the canal length. The measurements obtained through AI were then compared with those measured using RVG software. The findings demonstrated a high level of agreement between the two methods, with accuracy values ranging from 96.93% to 99.5% and an average accuracy of approximately 98.39%. The AI-assisted system was able to provide consistent and reliable measurements while minimizing manual intervention. Within the limitations of this study, the proposed AI model appears to be a promising tool for improving the precision and reproducibility of working length determination in endodontic practice.

Keywords: Artificial intelligence, endodontic working length, convolutional autoencoder, digital radiography, root canal segmentation

Introduction

Endodontic treatment is primarily aimed at preserving natural teeth by eliminating infection from the root canal system and preventing reinfection. For successful root canal therapy, accurate cleaning, shaping, and obturation of the canal space are essential. Among these steps, determination of the correct working length plays a crucial role in achieving favorable treatment outcomes. Working length refers to the distance from a fixed coronal reference point to the point where canal preparation and obturation should ideally terminate. If the working length is inaccurately determined, it may lead to incomplete cleaning of the canal or damage to the periapical tissues. Over-instrumentation beyond the apical constriction can result in extrusion of debris and irrigants into surrounding tissues, while under-instrumentation may leave residual microorganisms within the canal system, increasing the risk of persistent infection and treatment failure.

Over the years, several methods have been used for working length determination, including tactile sensation, conventional radiography, digital radiography, and electronic apex locators. Among these, radiographic evaluation remains one of the most commonly used techniques in routine clinical practice because of its accessibility and simplicity. However, radiographs provide only a two-dimensional image of a three-dimensional structure and are often affected by distortion, anatomical superimposition, and variations in angulation. In addition, interpretation of radiographs can vary between operators, making the process subjective and sometimes inconsistent. Although electronic apex locators have improved the accuracy of working length assessment, their readings may still be influenced by factors such as open apices, root resorption, metallic restorations, and excessive canal moisture.

With the rapid advancement of digital technology, artificial intelligence (AI) has emerged as a promising tool in healthcare and dentistry. Artificial intelligence refers to computer systems that can mimic human learning and decision-making processes. In dental imaging, deep learning models such as convolutional neural networks (CNNs) have shown excellent performance in identifying anatomical structures and detecting pathologies on radiographs. AI has already been applied in areas such as caries detection, diagnosis of periapical lesions, periodontal bone assessment, and identification of root canal morphology. These systems have the potential to improve diagnostic precision while reducing operator dependency and human error.

The application of artificial intelligence in endodontics is gaining increasing attention because automated image analysis may provide more objective and reproducible measurements compared to conventional methods. By combining image preprocessing, segmentation, and contour-based analysis, AI systems may be capable of accurately tracing the root canal path and estimating working length from diagnostic radiographs. Therefore, the present study was undertaken to evaluate the accuracy of measuring endodontic working length using an artificial intelligence-based approach and to compare the AI-generated measurements with conventional RVG measurements.

Aim of the Study

To evaluate the accuracy of measuring endodontic working length from diagnostic radiographs using artificial intelligence.

Objectives

1. To develop an AI-based deep learning framework for working length determination.
2. To segment root canals from diagnostic radiographs using a convolutional autoencoder model.
3. To compare AI-derived working length measurements with RVG-based measurements.
4. To assess the accuracy and reproducibility of the AI system.

Materials and Methods

Study Design

The present study was designed as an in vitro observational study to evaluate the accuracy of artificial intelligence in measuring endodontic working length from diagnostic dental radiographs. The study utilized digital periapical radiographs of single-rooted teeth to develop and validate a deep learning-based framework for automated working length determination. In vitro studies provide a controlled environment that minimizes clinical variables and allows standardized evaluation of image-processing algorithms and AI-based models. Diagnostic radiography was selected as the imaging modality because intraoral periapical radiographs remain one of the most commonly used methods for working length assessment in routine endodontic practice due to their accessibility, low cost, and diagnostic reliability.

Dataset Creation

Image Acquisition

Digital dental radiographs were collected from the departmental RVG software database and stored securely in Google Drive for preprocessing and analysis. The radiographs were available in PNG and JPG formats, which are commonly used digital image formats in dental imaging. PNG images preserve high-resolution details without compression loss, while JPG images provide reduced storage size with acceptable image quality. Previous studies have shown that high-resolution digital radiographs improve visualization of fine anatomical structures such as the apical constriction and root canal morphology, thereby enhancing the performance of AI-based image analysis systems.

The use of digital radiography offers several advantages over conventional film-based imaging, including reduced radiation exposure, immediate image acquisition, image enhancement capabilities, and improved diagnostic accuracy. These features make digital radiographs suitable for integration with artificial intelligence and deep learning algorithms.

Inclusion Criteria

The radiographs included in the study fulfilled the following criteria:

- Single-rooted teeth
- Clearly visible apical constriction
- Adequate radiographic contrast and exposure
- Minimal image artefacts

Single-rooted teeth were selected to minimize anatomical variability and facilitate accurate segmentation of the root canal system. Radiographs with clearly identifiable apical anatomy were included because accurate localization of the apical constriction is essential for precise working length determination. Images with poor contrast, distortion, excessive noise, or processing artefacts were excluded, as image quality significantly influences the accuracy of convolutional neural network (CNN)-based segmentation models. Previous evidence has demonstrated that optimal image quality enhances feature extraction and improves the reliability of AI-assisted diagnostic systems in dentistry.

Image Preprocessing

Prior to training the deep learning model, all radiographs underwent a standardized preprocessing pipeline to improve image quality, reduce variability, and optimize model performance. Image preprocessing is considered a critical step in deep learning workflows because it enhances relevant anatomical features while minimizing unwanted noise and inconsistencies. Standardization also improves model convergence during training and reduces computational complexity.

Resizing

All radiographic images were resized to 256 × 256 pixels before being fed into the neural network model. Image resizing reduces computational load and ensures uniformity across the dataset, allowing efficient processing during model training. Standardized image dimensions are important in convolutional neural networks because inconsistent image sizes may affect feature extraction and learning efficiency. Previous deep learning studies in medical and dental imaging have demonstrated that resizing images to fixed dimensions improves processing speed while maintaining adequate anatomical detail for segmentation tasks.

Contrast Enhancement

Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to all images using a clip limit of 2.0 and an 8 × 8 tile grid. CLAHE is an advanced contrast enhancement technique that improves local contrast and enhances the visibility of subtle anatomical structures without excessive amplification of image noise. Unlike conventional histogram equalization, CLAHE prevents over-enhancement in homogeneous regions by limiting contrast amplification.

In endodontic radiographs, visualization of the root canal outline and apical region can often be compromised due to overlapping anatomical structures and varying exposure conditions. Previous studies have reported that CLAHE significantly improves edge definition and canal visibility in dental radiographs, thereby enhancing the performance of segmentation algorithms and AI-based diagnostic systems. Improved contrast enhancement allows the neural network to more effectively identify canal boundaries and anatomical landmarks required for accurate working length determination.

Input image

Normalization

Following contrast enhancement, pixel intensity values of all images were normalized to a range between 0 and 1. Normalization is an essential preprocessing step in deep learning because it reduces variations in pixel intensity distributions and facilitates stable gradient propagation during neural network training. By scaling the input values to a standardized range, the model can learn more efficiently and achieve improved convergence during optimization.

Evidence from deep learning literature indicates that normalization improves training stability, reduces computational errors, and enhances overall model accuracy in medical image analysis. In the present study, normalization ensured consistency among radiographs obtained under different imaging conditions and contributed to reliable feature extraction during segmentation.

Proposed Architecture

The proposed artificial intelligence framework was designed as a multi-stage pipeline for automated endodontic working length determination from diagnostic radiographs. The framework consisted of four major stages: image acquisition, image preprocessing, root canal segmentation, and working length estimation. This sequential architecture was developed to ensure accurate extraction of canal morphology and reliable length calculation while minimizing operator intervention. Similar multistage deep learning frameworks have demonstrated promising results in medical and dental image analysis by improving feature extraction and segmentation accuracy.

Image Acquisition

High-resolution digital periapical radiographs were collected using the departmental RVG system and digitized for computational analysis. Digital image acquisition provides enhanced image manipulation capabilities, including magnification, contrast adjustment, and image enhancement, which improve the visualization of root canal anatomy. Previous studies have reported that digital radiography serves as a suitable imaging modality for AI-assisted endodontic diagnosis due to its consistency and compatibility with deep learning algorithms.

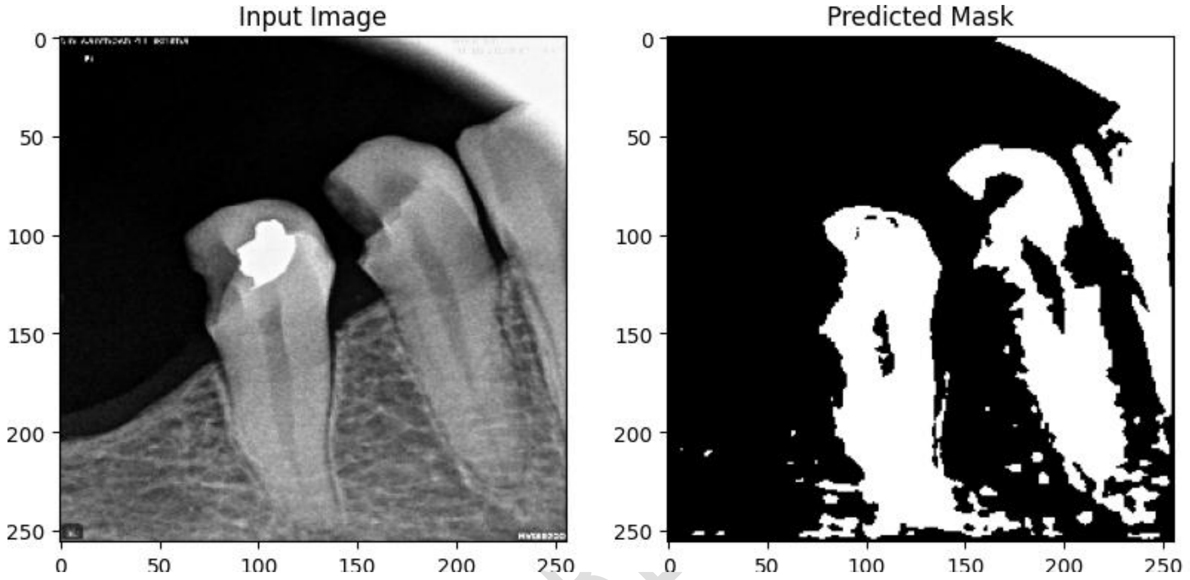
Image Preprocessing

The acquired radiographs underwent preprocessing procedures including resizing, contrast enhancement, and normalization before being introduced into the neural network. Preprocessing improves image uniformity and enhances relevant anatomical features while reducing noise and inconsistencies. Standardized preprocessing is essential in deep learning systems because variations in image intensity and dimensions can negatively influence model training and segmentation accuracy.

Contrast enhancement using CLAHE improved the visibility of canal boundaries and apical regions, thereby facilitating more precise feature extraction by the neural network. Image normalization further stabilized the learning process by maintaining uniform pixel intensity distribution across the dataset.

Root Canal Segmentation

Root canal segmentation was performed using a convolutional autoencoder model. Segmentation is a critical step in AI-assisted image analysis because accurate identification of the root canal space directly influences the precision of working length estimation. Convolutional neural networks (CNNs) are widely used in medical imaging because of their ability to automatically learn hierarchical image features such as edges, shapes, and anatomical structures.



Convolutional Autoencoder for Segmentation

A four-layer convolutional autoencoder was implemented to generate binary segmentation masks of the root canal system. The autoencoder architecture consisted of two major components: an encoder and a decoder.

The encoder extracted essential image features through convolutional operations and reduced the spatial dimensions using pooling layers. This process enabled the model to learn important anatomical patterns related to the root canal system while reducing redundant information. The decoder reconstructed the segmented image from the extracted features and generated a binary mask highlighting the canal region.

Autoencoder-based segmentation models are considered computationally efficient and suitable for biomedical image segmentation tasks, especially in situations involving limited datasets. Previous studies have shown that convolutional autoencoders can achieve reliable segmentation performance in dental radiographs due to their ability to capture structural details while preserving image continuity.

Model Architecture

The convolutional autoencoder architecture used in the present study is represented below:

```
model = Sequential([
    Conv2D(64, (3,3), activation='relu', padding='same',
input_shape=(256,256,1)),
    MaxPooling2D((2,2)),
    UpSampling2D((2,2)),
    Conv2D(1, (3,3), activation='sigmoid', padding='same')
])
```

The first convolutional layer utilized 64 filters with a 3 × 3 kernel size and ReLU activation to extract low-level image features such as canal edges and anatomical contours. Max pooling reduced image dimensions and computational complexity while preserving important features. The upsampling layer restored the spatial dimensions of the segmented output image. Finally, a sigmoid activation function was used in the output layer to generate a binary probability map representing the segmented root canal region.

The use of ReLU activation functions improves computational efficiency and minimizes the vanishing gradient problem during training, whereas sigmoid activation is commonly used in segmentation tasks to classify pixels into foreground and background regions.

Working Length Measurement

Following segmentation, the binary canal mask underwent additional image processing procedures to estimate the endodontic working length accurately. Since root canals often exhibit curvature and anatomical complexity, linear measurements alone may not provide accurate length estimation. Therefore, skeletonization and contour-based analysis were incorporated into the framework to improve precision.

Skeletonization

Morphological thinning techniques were applied to reduce the segmented canal mask into a one-pixel-wide skeletal representation of the canal path. Skeletonization preserves the original geometry and curvature of the root canal while simplifying the structure for length calculation.

This technique is particularly beneficial in curved canals because it allows accurate tracing of the canal trajectory without distortion. Evidence from image-processing literature suggests that skeletonization improves path analysis and geometric measurement accuracy in biomedical imaging applications.

Contour Detection

After skeletonization, contour detection was performed using the OpenCV findContours function to identify the longest continuous canal path. Contour detection algorithms analyze object boundaries and trace the canal outline from the coronal reference point to the apical region.

Among multiple detected contours, the longest continuous contour was selected because it most accurately represented the true canal trajectory. OpenCV-based contour analysis has been widely used in image-processing applications due to its efficiency in identifying anatomical structures and boundaries in grayscale medical images.

Arc Length Calculation

The working length was calculated by measuring the arc length of the detected contour. Unlike straight-line distance measurements, arc length estimation follows the natural curvature of the canal and therefore provides more anatomically accurate measurements.

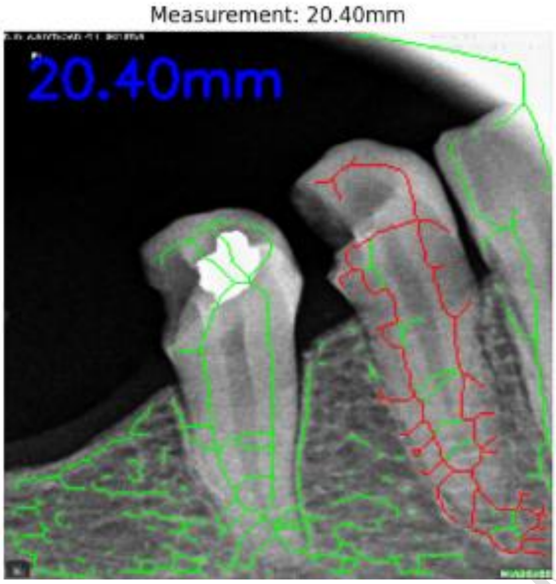
This method is particularly advantageous in curved root canals where conventional radiographic estimation may underestimate the actual canal length. Previous studies have demonstrated that contour-based arc length calculation improves measurement reliability in curved anatomical structures and enhances the precision of automated image-analysis systems.

$$\text{Length}_{\text{mm}} = \text{Arc Length}_{\text{px}} \times 0.019$$

Validation

The accuracy of the AI-generated measurements was validated through visual inspection and comparison with RVG-based measurements by experienced dental professionals. Expert validation is essential in AI-based diagnostic systems to ensure clinical relevance and reliability of the predicted outputs.

A representative sample generated by the model demonstrated a canal length measurement of 20.40 mm, which closely corresponded with clinically expected values. The high level of agreement between AI-derived and conventional measurements indicated the reliability of the proposed framework for endodontic working length determination.



Statistical Analysis

The working length measurements obtained using the artificial intelligence (AI) system were compared with measurements obtained using RVG software, which served as the reference standard. The accuracy of the AI model was assessed by calculating the percentage agreement between the AI-derived measurements and RVG measurements. Statistical evaluation of accuracy is essential in validating the reliability and clinical applicability of automated diagnostic systems. High agreement between AI-generated and conventional measurements indicates the precision and consistency of the proposed framework.

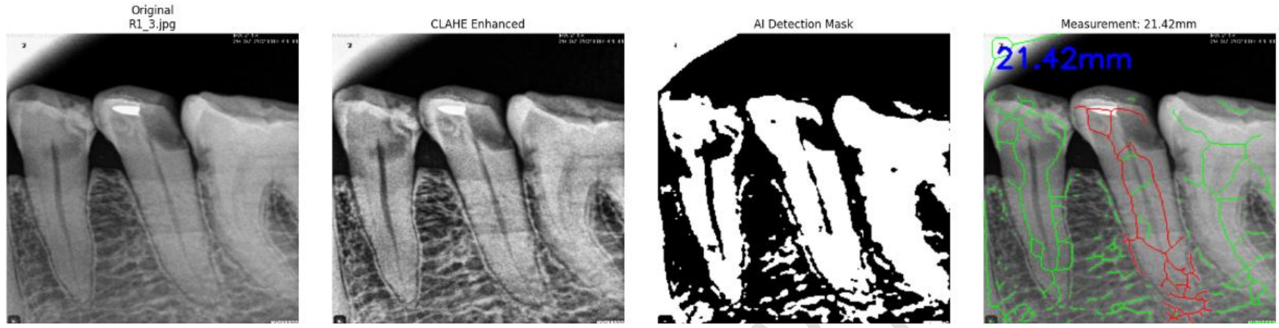
The accuracy percentage was calculated using the following formula:

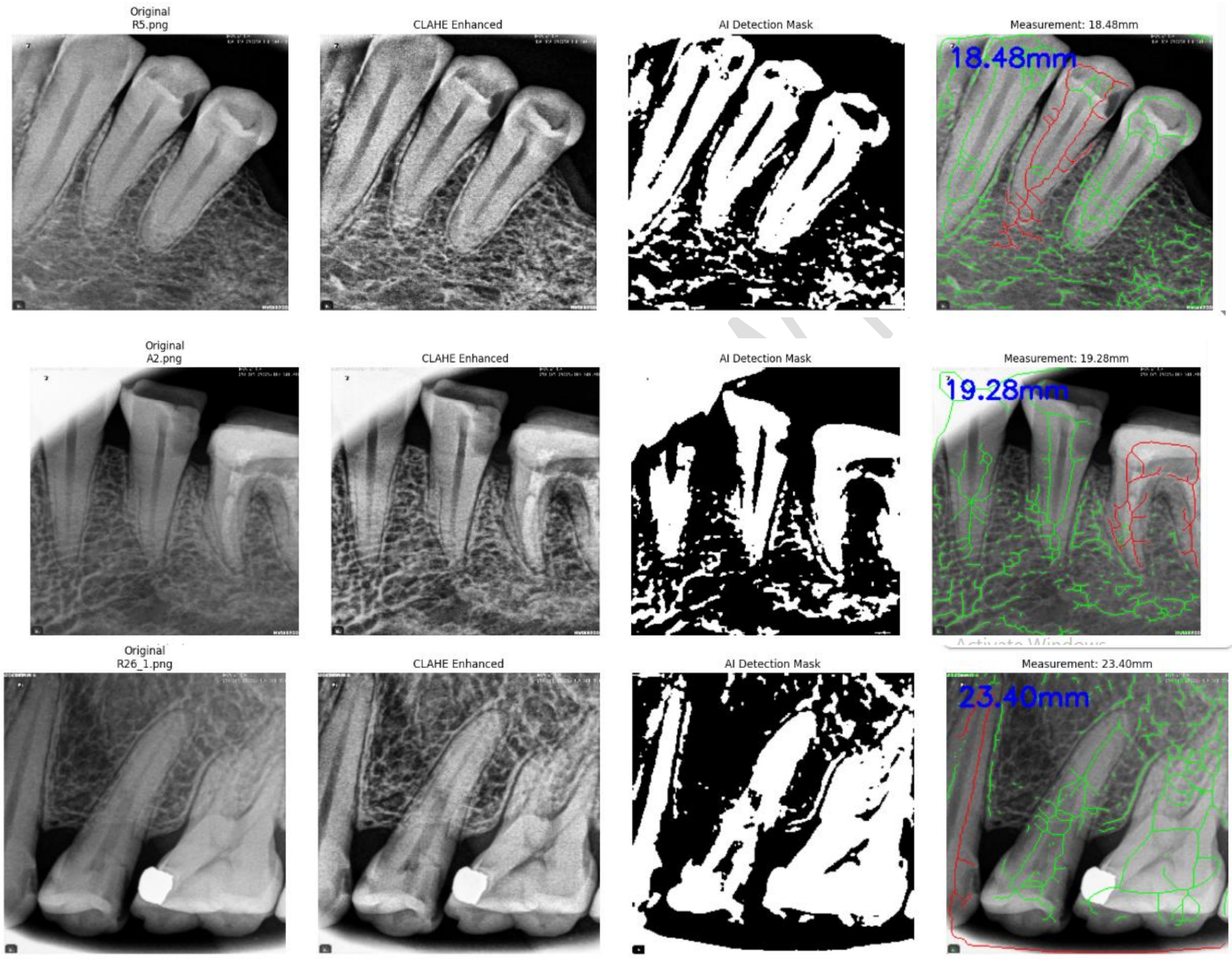
$$\text{Accuracy} = \left(1 - \frac{(True\ Length - Predicted\ \ length)}{True\ Length}\right) \times 100$$

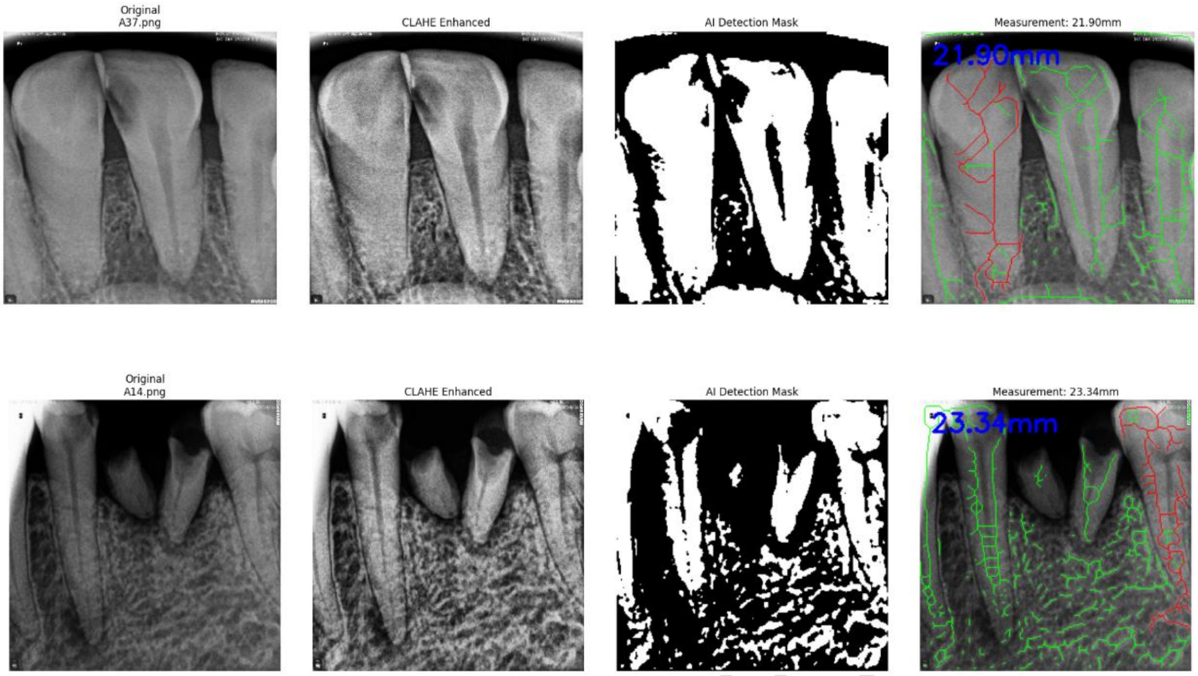
This formula was used to determine how closely the AI-generated working length corresponded to the RVG-based measurement for each sample image. Values approaching 100% indicated a high level of agreement and greater measurement accuracy.

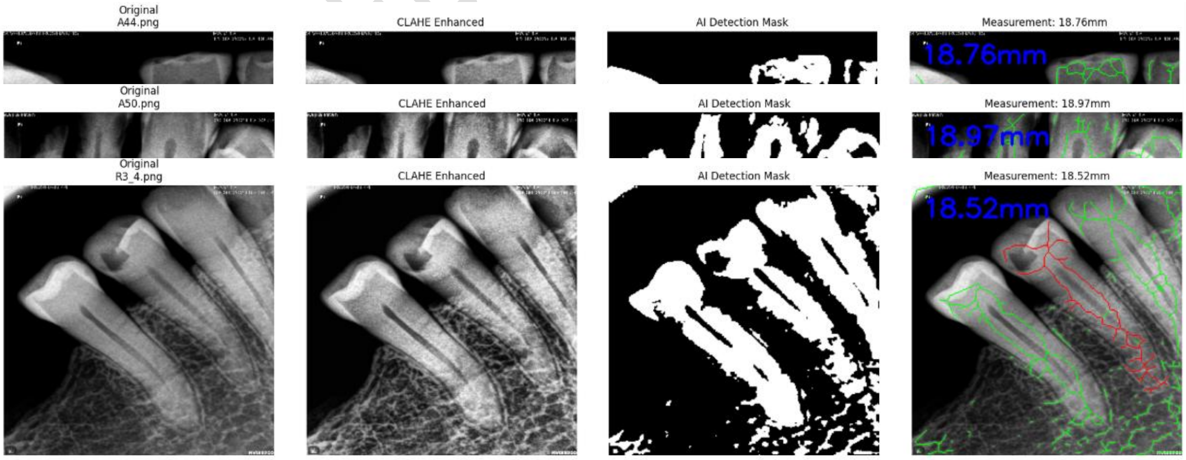
Results

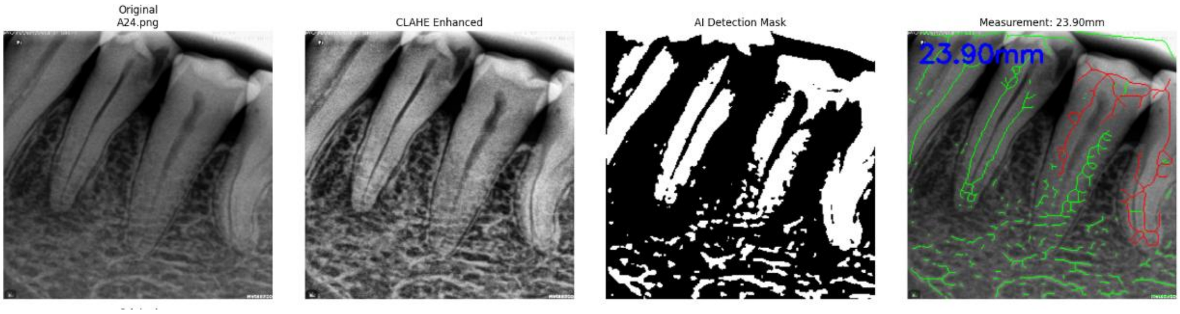
The AI-based system demonstrated a high level of accuracy in determining endodontic working length from diagnostic radiographs. Comparison between AI-derived measurements and RVG measurements showed minimal variation across the evaluated samples, indicating reliable performance of the proposed deep learning framework.




Original
R5.png
CLAHE Enhanced
AI Detection Mask
Measurement: 18.48mm
18.48mm
Original
A2.png
CLAHE Enhanced
AI Detection Mask
Measurement: 19.28mm
19.28mm
Original
R26_1.png
CLAHE Enhanced
AI Detection Mask
Measurement: 23.40mm
23.40mm


Original
A37.png
CLAHE Enhanced
AI Detection Mask
Measurement: 21.90mm
21.90mm
Original
A14.png
CLAHE Enhanced
AI Detection Mask
Measurement: 23.34mm
23.34mm

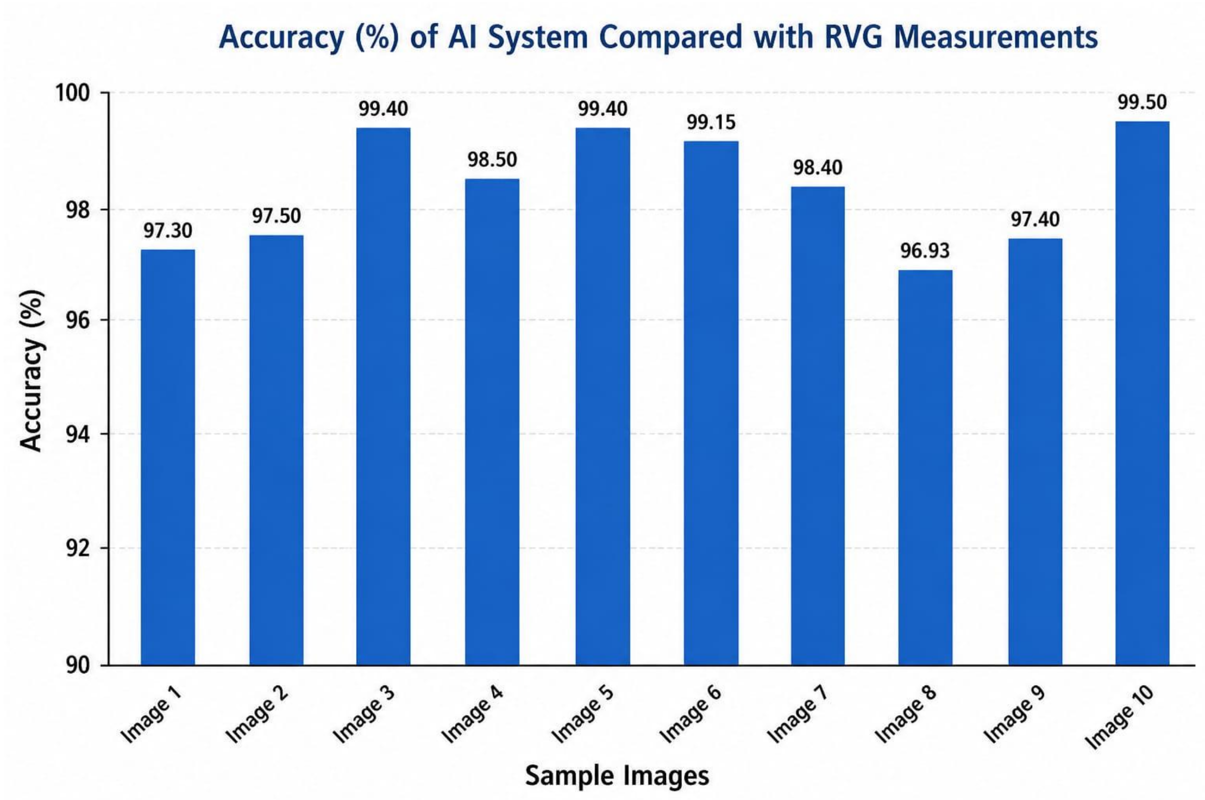

Original
A44.png
CLAHE Enhanced
AI Detection Mask
Measurement: 18.76mm
18.76mm
Original
A50.png
CLAHE Enhanced
AI Detection Mask
Measurement: 18.97mm
18.97mm
Original
R3_4.png
CLAHE Enhanced
AI Detection Mask
Measurement: 18.52mm
18.52mm



RESULTS

Comparison of Working Length Measurements Obtained by AI System and RVG Software

Sample Image	RVG Measurement (mm)	AI Measurement (mm)	Accuracy (%)
Image 1	22.0	21.4	97.30
Image 2	24.0	23.4	97.50
Image 3	18.5	18.4	99.40
Image 4	19.5	19.2	98.50
Image 5	22.0	21.9	99.40
Image 6	23.5	23.3	99.15
Image 7	19.0	18.7	98.40
Image 8	19.5	18.9	96.93
Image 9	19.0	18.5	97.40
Image 10	24.0	23.9	99.50
Mean Accuracy of AI System: 98.39%			



Discussion

Accurate working length determination is one of the most critical factors influencing the success of endodontic treatment because it directly affects cleaning, shaping, disinfection, and obturation of the root canal system. The apical constriction is considered the ideal endpoint for instrumentation and obturation, as preparation beyond this point may cause periapical tissue injury, postoperative pain, and extrusion of debris, whereas instrumentation short of this point may leave residual microorganisms and necrotic tissue within the canal. Sjögren et al. demonstrated that teeth obturated within **0**–2 mm of the radiographic apex showed significantly higher healing rates than overfilled or underfilled canals, emphasizing the importance of accurate working length determination.

Conventional radiographic techniques remain the most commonly used method for working length assessment because they are simple, inexpensive, and readily available. However, radiographs produce a two-dimensional image of a three-dimensional structure, making them susceptible to anatomical superimposition, image distortion, magnification errors, and variations in angulation. Forsbergreported that changes in horizontal angulation can significantly alter the perceived root length, affecting measurement accuracy. Likewise, Walton and Torabinejad emphasized that radiographic interpretation is highly operator-dependent, resulting in interobserver variability and inconsistent measurements.

Electronic apex locators (EALs) have considerably improved the accuracy of working length determination and reduced reliance on radiographs. Kobayashi and Suda reported that modern apex locators can achieve accuracy rates exceeding 90% under ideal clinical conditions. Nevertheless, their performance may be compromised in the presence of open apices, root resorption, metallic restorations, excessive canal moisture, or electrolyte imbalance. Moreover, EALs provide limited information regarding root canal anatomy and surrounding periapical structures. Therefore, integrating artificial intelligence with radiographic assessment has the potential to complement existing methods and improve diagnostic reliability.

Artificial intelligence (AI), particularly deep learningand convolutional neural networks(CNNs), has emerged as a transformative technology in dental imaging. CNNs automatically learn hierarchical image features, enabling accurate identification of anatomical structures and pathological changes without extensive manual intervention. In dentistry, AI has shown promising applications in detecting dental caries, periodontal bone loss, periapical lesions, vertical root fractures, root morphology, and treatment planning. Schwendicke et al. reported that AI-based diagnostic systems can achieve accuracy comparable to experienced clinicians while reducing inter-observer variability and improving diagnostic consistency.

The present study evaluated an AI-assisted framework for automated working length determination and demonstrated a mean accuracy of 98.39%, with values ranging from 96.93% to 99.5%, indicating excellent agreement with conventional RVG measurements. These findings suggest that AI can reliably estimate working length with minimal operator intervention. Similar observations have been reported by Saghiri et al., who successfully used artificial neural networks to identify apical foramina and canal pathways, and Orhan et al., who demonstrated high sensitivity and specificity of deep learning models in detecting periapical lesions on radiographs and CBCT images.

The excellent performance observed in the present study can largely be attributed to the multistage AI frameworkemployed. Image preprocessing played a crucial role by improving radiographic quality before segmentation. Contrast Limited Adaptive Histogram Equalization (CLAHE)enhanced local contrast, making canal boundaries and the apical region more clearly visible while minimizing excessive image noise. Improved contrast facilitated more accurate feature extraction by the neural network and enhanced segmentation performance.

Additionally, image normalization and resizing standardized the dataset by reducing variations in image intensity and dimensions. These preprocessing steps improved model convergence, stabilized neural network training, and enhanced reproducibility across radiographs acquired under different imaging conditions.

The convolutional autoencoder served as the core segmentation model. Autoencoders efficiently learn compressed image representations while preserving important anatomical details, making them suitable for biomedical image segmentation, particularly when datasets are relatively small. Although U-Net is widely regarded as the gold standard for medical image segmentation, convolutional autoencoders offer lower computational requirements while maintaining reliable segmentation accuracy. Chen et al. similarly reported satisfactory performance of autoencoder-based segmentation models in dental radiographic analysis.

A major strength of the proposed framework was its ability to accurately measure curvedroot canals. Conventional radiographic methods generally estimate working length using straight-line measurements, which may underestimate the actual canal length in curved canals. To overcome this limitation, the present study combined skeletonization**,** OpenCV-based contour detection, and arc-length analysis. Skeletonization reduced the segmented canal to a one-pixel-wide centerline while preserving its natural curvature. Contour detection identified the true canal pathway, and arc-length measurement followed the curved trajectory, resulting in a more anatomically accurate estimation of working length. Similar contour-based approaches have been successfully applied in biomedical imaging for measuring curved anatomical structures such as blood vessels and nerve pathways.

The findings further support the expanding role of AI in endodontics. Systematic reviews by Khanagar et al**.** and Hung et al. concluded that AI has significant potential to improve radiographic interpretation, automated diagnosis, treatment planning, and clinical decision-making. AI-assisted working length determination may reduce operator dependency, improve standardization, shorten clinical procedures, and serve as an effective educational tool for undergraduate students and less experienced clinicians.

Despite these promising findings, certain limitations should be acknowledged. The study included only single-rooted teeth, reducing anatomical complexity and facilitating segmentation. The performance of the proposed framework should be further evaluated in multi-rooted teeth, severely curved canals, calcified canals, and teeth with resorptive defects. Furthermore, the relatively limited dataset may affect model generalizability, highlighting the need for larger multicenter datasets for robust clinical validation.

Another limitation was the use of RVG measurements as the reference standard. Although routinely used in clinical practice, RVG measurements remain susceptible to projection errors and operator bias. Future studies should compare AI-derived measurements with micro-computed tomography (micro-CT) or direct canal measurements, which provide superior three-dimensional anatomical accuracy and are considered more reliable reference standards.

Future research should focus on incorporating advanced segmentation architectures such as U-Net, attention-based CNNs, and transformer-based deep learning models, which have demonstrated superior performance in complex medical image segmentation tasks. Integration of CBCT imaging may further improve three-dimensional working length estimation, while real-time incorporation of AI into RVG software could facilitate chairside automated working length measurementduring routine endodontic treatment.

Overall, the findings of the present study support the growing evidence that artificial intelligence can serve as a reliable adjunctive tool for endodontic working length determination. By combining advanced image preprocessing, automated segmentation, curvature analysis, and contour-based measurement techniques, the proposed framework achieved high accuracy and reproducibility. With further validation on larger and more diverse clinical datasets, AI-assisted systems have the potential to enhance diagnostic precision, reduce operator dependency, standardize endodontic procedures, and improve long-term treatment outcomes.

Conclusion

Within the limitations of the present study, the proposed artificial intelligence-based framework demonstrated a high level of accuracy in determining endodontic working length from diagnostic radiographs. The integration of image preprocessing, convolutional autoencoder-based segmentation, skeletonization, and contour-based arc length analysis enabled reliable identification and measurement of the root canal pathway, even in curved canals. The AI-generated measurements showed strong agreement with conventional RVG measurements, with a mean accuracy of approximately 98.39%, indicating the potential of deep learning systems to provide consistent and reproducible results.

The findings of this study support the growing role of artificial intelligence in endodontics and dental radiographic analysis. AI-assisted working length determination may reduce operator dependency, minimize subjective interpretation errors, and improve clinical efficiency during endodontic procedures. Furthermore, automated systems may serve as valuable adjunctive tools for clinicians and educational aids for less experienced practitioners.

Although the present framework demonstrated promising performance, further research involving larger datasets, multi-rooted teeth, and complex canal anatomies is required to improve generalizability and clinical applicability. Future incorporation of advanced deep learning architectures and three-dimensional imaging modalities such as CBCT may further enhance diagnostic precision. Overall, artificial intelligence has the potential to become an important supportive technology in modern endodontic practice, contributing to more accurate diagnosis, standardized treatment procedures, and improved patient outcomes.

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