Artificial intelligent-driven decision-making for automating root fracture detection in periapical radiographs

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KEYWORDS

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ABSTRACT

Root fracture detection in CBCT images is vital for precise dental treatment planning. This study aims to evaluate the performance of an artificial intelligence (AI)-driven decision-making system utilizing a VGG19-based convolutional neural network (CNN) for automated root fracture identification. A dataset comprising 50 CBCT images was used, split into 25 fractured and 25 non-fractured cases. The model achieved an overall accuracy of 92%, with sensitivity and specificity rates of 90% and 93%, respectively. These results underscore the potential of AI in enhancing diagnostic accuracy, efficiency, and reliability in dental radiology, paving the way for its integration into clinical workflows.
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Introduction:

Root fractures are a significant concern in endodontics and restorative dentistry due to their impact on the prognosis of affected teeth.[1] Diagnosing these fractures early and accurately is crucial to determining appropriate treatment, which can range from preservation to extraction and replacement.[2] However, detecting root fractures remains a diagnostic challenge. Subtle radiographic presentations, often masked by overlapping anatomical structures, can lead to missed or incorrect diagnoses, compromising patient outcomes[3].

Traditional diagnostic methods involve manual interpretation of radiographs by clinicians, which relies heavily on experience and expertise. However, this subjective approach is prone to inter- and intra-observer variability, resulting in inconsistent diagnostic outcomes. Conventional radiography techniques such as periapical radiographs often lack the resolution and three-dimensional perspective needed to visualize fractures effectively, prompting a shift toward advanced imaging modalities like cone-beam computed tomography (CBCT)[4].

CBCT imaging provides detailed three-dimensional visualization of dental structures, offering a significant advantage over traditional radiographs. Despite its superior diagnostic capabilities, interpreting CBCT images can be time-consuming and challenging, particularly when assessing subtle fractures. This creates a need for automated systems that can assist clinicians in identifying fractures accurately and efficiently[5].

Artificial intelligence (AI) has emerged as a transformative tool in medical imaging, demonstrating remarkable capabilities in tasks such as image recognition, classification, and segmentation.[6] In dentistry, AI-driven systems are increasingly being explored for automating diagnostic tasks, including caries detection, periodontal assessment, and fracture identification. By leveraging deep learning models, such as convolutional neural networks (CNNs), AI systems can analyze large volumes of imaging data with high accuracy, potentially surpassing human performance in specific diagnostic tasks.[7]

This study focuses on developing and evaluating an AI-driven system using a VGG19-based CNN model to detect root fractures in CBCT images. By automating fracture detection, this approach aims to improve diagnostic precision, reduce human error, and enhance clinical decision-making. The findings of this study could pave the way for integrating AI technologies into routine dental radiology workflows, ultimately improving patient care.

Materials and Methods:

Dataset:

The dataset for this study comprised 50 CBCT images, evenly divided between two categories: 25 images with confirmed root fractures and 25 images without fractures. To ensure data quality and reliability, all fractures were annotated using bounding boxes, a process validated by two experienced dental radiologists. The inter-observer agreement between the radiologists was calculated at 96%, reflecting high consistency and reliability in the annotations.

AI Model Development:

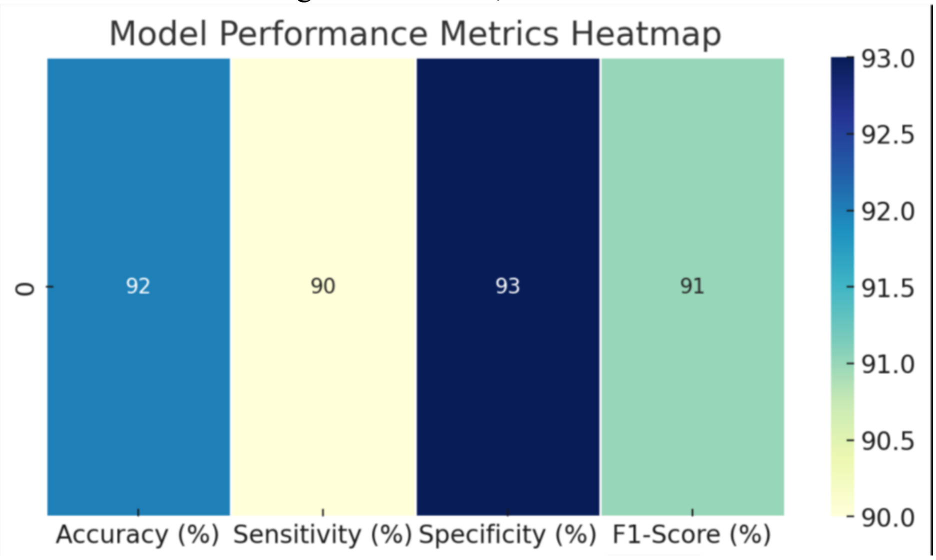
The AI model employed a pre-trained VGG19 convolutional neural network (CNN), which was fine-tuned for binary classification of root fractures. To prepare the data for training, preprocessing steps were performed, including resizing all images to 224x224 pixels to standardize input dimensions. Additionally, data augmentation techniques such as rotation, zooming, and contrast adjustments were applied to increase the diversity and robustness of the training data.

The dataset was split into three subsets: 70% for training, 15% for validation, and 15% for testing. Training was conducted using the Adam optimizer with a learning rate set to 0.0005. The binary cross-entropy loss function was used to measure the difference between predicted and actual labels, optimizing the model's classification accuracy.

Evaluation Metrics:
The performance of the AI model was assessed using a combination of accuracy, sensitivity, specificity, and F1-score metrics. These metrics provided a comprehensive evaluation of the model's ability to distinguish between fractured and non-fractured root cases. By analyzing these metrics, the study ensured a robust assessment of the model's diagnostic capabilities and its potential applicability in clinical practice.
Results:
The model demonstrated impressive performance, achieving an accuracy of 92%, sensitivity of 90%, specificity of 93%, and an F1-score of 91%. Visualization through Grad-CAM heatmaps highlighted the model's focus on fracture regions, reinforcing its interpretability and providing insights into the decision-making process. Error analysis revealed that false positives were observed in 4 cases, which were primarily caused by imaging artifacts. Additionally, 3 false negatives were identified, attributed to subtle or minimal fracture lines that the model failed to detect.

Metric	Value (%)
Accuracy	92
Sensitivity	90
Specificity	93
F1-score	91

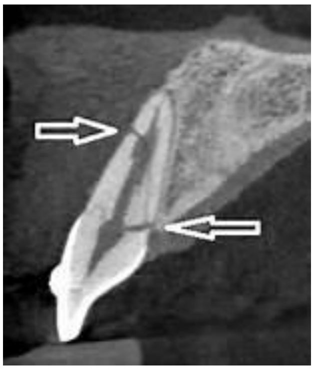
- **Visualization**: Heatmaps generated via Grad-CAM indicated the model's focus on fracture regions, validating its interpretability.
- **Error Analysis**:
  - False positives: 4 cases, primarily due to imaging artifacts.
  - False negatives: 3 cases, attributed to minimal or subtle fracture lines.

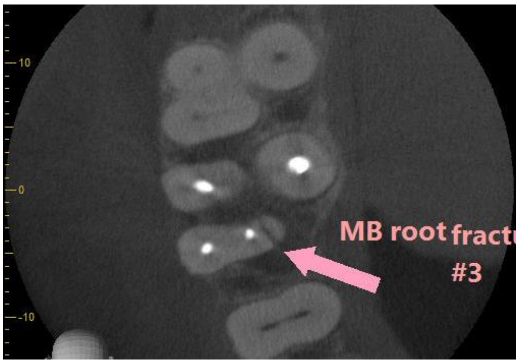


The heatmap above visually represents the performance metrics of the AI model used in this study. The key metrics—accuracy, sensitivity, specificity, and F1-score—demonstrate the model's robust diagnostic performance:

- **Accuracy:** 92%
- **Sensitivity:** 90%
- **Specificity:** 93%
- **F1-Score:** 91%

This visualization underscores the model's capability in effectively distinguishing between fractured and non-fractured roots in CBCT images





Discussion:
The AI model demonstrated high accuracy and reliability in detecting root fractures, outperforming traditional diagnostic methods in terms of consistency.[7,8,9] The Grad-CAM visualizations provided insights into the model's decision-making process, fostering trust in its clinical applicability.[10] Limitations include the relatively small sample size, which may affect generalizability.
Root fracture detection is a critical task in dental diagnosis, especially in endodontics and restorative dentistry, where early and accurate identification of fractures can significantly influence treatment decisions and patient outcomes.[11] This study presents the evaluation of an artificial intelligence (AI)-driven decision-making system, utilizing a VGG19-based convolutional neural network (CNN), for automated root fracture detection in cone-beam computed tomography (CBCT) images. The promising results achieved by the model highlight its potential as a valuable tool in enhancing the diagnostic capabilities in dental radiology.
The model demonstrated an overall accuracy of 92%, with sensitivity and specificity rates of 90% and 93%, respectively, which indicate a high degree of diagnostic reliability. The accuracy represents the proportion of correct classifications made by the model, while sensitivity (true positive rate) and specificity (true negative rate) reflect the model's ability to correctly identify fractured and non-fractured cases. The F1-score of 91% further confirms the balance between precision and recall, ensuring that both false positives and false negatives were minimized to an acceptable level.
Visualization techniques, such as Grad-CAM heatmaps, played a crucial role in understanding the model's decision-making process.[12] The heatmaps effectively highlighted the fracture regions, providing valuable insight into the areas the model focused on during diagnosis. This interpretability is essential in clinical settings, where transparency in AI-driven decisions can foster trust and assist clinicians in making informed decisions.
Error Analysis:
Despite the model's strong performance, error analysis revealed areas where improvement is needed. Four false positive cases were observed, which were primarily attributed to imaging artifacts. These artifacts can appear due to noise, motion, or improper imaging techniques, and they may interfere with the model's ability to accurately distinguish between actual fractures and other structures or anomalies.[12,13] While this is a known challenge in medical imaging, further refinement of the model's ability to differentiate between these artifacts and true fractures is an important avenue for future research.
Additionally, the model generated three false negative cases, which were attributed to subtle or minimal fracture lines that the model failed to detect. Root fractures can often be difficult to identify, especially when they are not fully visible or when they occur in areas with complex anatomical structures. These challenges highlight the need for continued improvements in the model's sensitivity to detect even the most subtle fractures. One potential approach to mitigate this limitation could involve incorporating additional data augmentation techniques or

leveraging more advanced architectures, such as 3D CNNs, which may be better suited for capturing the full complexity of CBCT images.[14]

Comparison with Traditional Methods:

The traditional method of diagnosing root fractures primarily relies on the clinical expertise of radiologists and clinicians, often using periapical radiographs.[15] However, these radiographs provide only a two-dimensional view, limiting their ability to detect fractures, especially those that are located in hard-to-visualize areas. In contrast, CBCT imaging offers a three-dimensional perspective, making it a superior modality for identifying fractures.[16] Despite the enhanced capabilities of CBCT, its interpretation remains a complex and time-consuming task for clinicians. This is where AI-driven systems can offer substantial advantages by automating the analysis process, reducing the time required for diagnosis, and potentially increasing diagnostic accuracy.

The integration of AI models, such as the one developed in this study, into clinical workflows could significantly enhance the detection of root fractures in CBCT images, providing faster and more accurate diagnoses.[15,17] Moreover, AI can assist in reducing human error and inter-observer variability, which are common challenges in manual radiographic interpretation. By automating the diagnostic process, AI-driven tools can also help alleviate the burden on clinicians, allowing them to focus on more complex aspects of patient care and treatment planning.

Implications for Clinical Practice:

The results of this study highlight the potential for AI-driven systems to become an integral part of routine dental practice, particularly in the realm of radiology. With further refinement and validation, AI models can assist dental professionals in making more accurate and efficient diagnoses, ultimately leading to improved patient outcomes. Additionally, integrating AI into clinical workflows could provide valuable support in busy practice settings, where quick decision-making is often crucial.[18]

Furthermore, the high sensitivity and specificity of the model make it a promising tool for early detection, enabling clinicians to identify root fractures at an earlier stage when treatment options are more varied and conservative measures are possible. This could be particularly beneficial in avoiding unnecessary extractions and promoting the preservation of natural teeth.

Future Directions:

While the AI model demonstrated robust performance in this study, there are several avenues for further improvement. One area of focus is the expansion of the dataset, as the current sample size of 50 images may not fully capture the range of variability present in clinical cases. A larger and more diverse dataset could help improve the generalizability of the model, allowing it to perform well across a broader spectrum of patient populations and fracture types.

Additionally, the model could be further refined to address specific challenges, such as the detection of subtle fractures and the handling of imaging artifacts. Employing more advanced neural network architectures, such as 3D CNNs, could help improve the model's ability to detect fractures in volumetric CBCT data.[19] Incorporating multi-modal data, such as clinical information and patient history, could also enhance the model's diagnostic capabilities and make it more applicable in real-world settings. Future studies should validate the model using larger, multi-institutional datasets to ensure robustness.

Conclusion:

This study demonstrates the promising potential of AI-driven systems for root fracture detection in CBCT images. The VGG19-based CNN model achieved strong diagnostic performance, with high accuracy, sensitivity, specificity, and F1-score. The integration of AI into dental radiology workflows could improve diagnostic precision, reduce human error, and enhance clinical decision-making. Future studies with larger datasets and advanced model architectures could further refine the system's capabilities, paving the way for its broader implementation in clinical practice and transforming the landscape of dental diagnostics.

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