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Classification & Detection of Periapical Lesion using Machine Learning

Name: Akansha Jadhav, Shivtej Patil , Siddhi Thawal, Vishal Pasodi
Guide Name: Vaishali Latke

Abstract:
The human teeth are the hardest structures in the body, with enamel as their outermost layer. Speech is greatly influenced by teeth, which typically emerge by the age of 13. However, by their mid-30s, more than 80% of people in the United States have at least one cavity, making tooth decay one of the most prevalent chronic diseases affecting individuals of all ages. Dental decay, which takes the form of pit and fissure, root, or smooth surface decay, can be avoided with good oral hygiene practices and regular dental cleanings.

Periapical lesions can develop due to various causes, such as trauma, inflammation, or differences in the tooth's surrounding tissue, with treatment options varying depending on the lesion's size or location. Endodontics, or root canal therapy, is a dental technique used to treat infections in the tooth's pulp, allowing the preservation of the tooth that might otherwise need to be entirely extracted.

Dental disorders are often diagnosed using X-ray imaging, and the segmentation and categorization of dental abnormalities using neural networks are proving beneficial to the dental field. Various machine learning algorithms are used to categorize and identify dental abnormalities, with CNNs being the preferred network architecture for recognizing objects in tasks like image recognition and pixel data processing.

In summary, good oral hygiene practices and regular dental check-ups can help prevent tooth decay, while endodontics can save a tooth from extraction. The use of neural networks for dental abnormality diagnosis is proving beneficial to the dental field, with CNNs being the preferred network architecture for recognizing dental abnormalities.

Keywords: Tooth anomaly, Root canal, Periapical lesions, Endodontic therapy, Convolutional neural networks, X-ray images, Dental cavities.

Introduction:

In this article, we will discuss the classification and detection of periapical lesions using machine learning. We will start by providing an overview of periapical lesions, including their causes, symptoms, and traditional diagnostic methods. We will then introduce machine learning and its potential application in dental diagnosis. We will also discuss the different machine learning algorithms and techniques used for detecting and classifying periapical lesions.

Next, we will highlight the advantages of using machine learning in periapical lesion diagnosis, including increased accuracy, speed, and consistency. We will also discuss the potential challenges and limitations of using machine learning, such as the need for high-quality training data and the potential for bias in algorithm design.

Finally, we will review recent studies that have applied machine learning to periapical lesion detection and classification, highlighting the accuracy and potential for real-world implementation. We will conclude by summarizing the potential benefits of using machine learning in periapical lesion diagnosis and highlighting future research directions.

Overall, this article aims to provide a comprehensive overview of the use of machine learning in periapical lesion detection and classification, and its potential to improve dental diagnosis and patient outcomes.

Methodology:

The methodology for using CNNs for the classification and detection of periapical lesions involves several steps, which can be summarized as follows:

Data collection: Collect high-quality periapical radiographs that have been labeled as either positive (lesion present) or negative (lesion absent) for the presence of periapical lesions. The dataset should be large enough to cover a diverse range of lesions and non-lesions.

Data preprocessing: Preprocess the data by cropping the images to the region of interest (ROI), resizing the images to a standard size, and normalizing the pixel values.

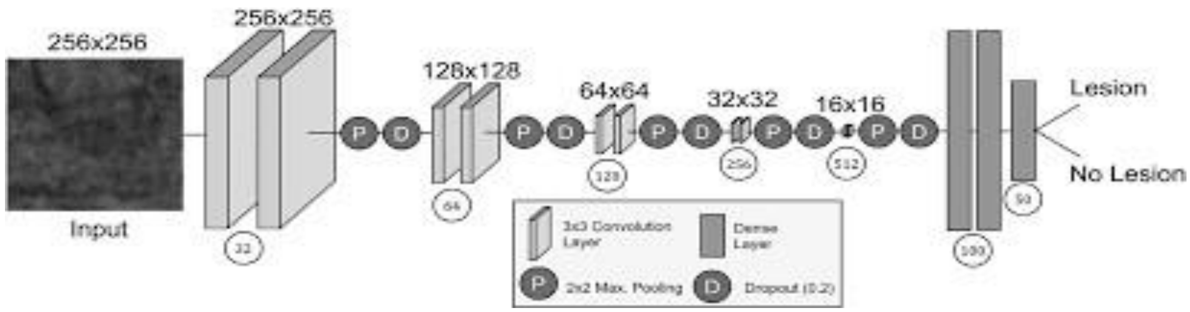
Model architecture: Design a CNN architecture that can effectively learn the features and patterns in the periapical radiographs. The architecture may include convolutional layers, pooling layers, activation functions, and fully connected layers.

Training the model: Train the CNN model on the labeled dataset. During training, the model learns to classify the images as positive or negative based on the labeled data.**Testing and validation:** Evaluate the trained model on a separate set of periapical radiographs that were not used during training. This helps to determine the accuracy of the model in detecting and classifying periapical lesions.

Optimization: Optimize the model by adjusting the hyperparameters and tweaking the architecture to improve its accuracy.

Deployment: Once the model has been optimized, it can be deployed in a clinical setting to assist in the detection and classification of periapical lesions in radiographs.

Overall, the methodology for using CNNs for the classification and detection of periapical lesions involves a combination of data collection, preprocessing, model architecture design, training, testing and validation, optimization, and deployment.



The performance was evaluated using the following metrics:
• True positives (TP): the number of correctly classified positive cases.
• True negatives (TN): the number of correctly classified negative cases.
• False positives (FP): the number of incorrectly classified positive cases.
• False negatives (FN): the number of incorrectly classified negative cases.

These metrics were used to calculate several performance measures, such as sensitivity (TP rate), specificity (TN rate), accuracy, precision, and F1 score. Sensitivity is the proportion of actual positive cases that were correctly classified as positive, while specificity is the proportion of actual negative cases that were correctly classified as negative. Precision is the proportion of true positive cases among all positive predictions, while the F1 score is the harmonic mean of precision and sensitivity.

For the detection task of periapical lesions, the expert and system annotations were deemed to agree if they intersected substantially. The performance was evaluated using the following metrics:
• True positives (TP): the number of correctly detected lesions.
• True negatives (TN): the number of correctly detected non-lesions.
• False positives (FP): the number of incorrectly detected lesions.
• False negatives (FN): the number of missed lesions.

These metrics were used to calculate several performance measures, such as sensitivity, specificity, accuracy, precision, and F1 score.
Overall, the performance analysis involved comparing the annotations made by the system and the experts, identifying cases of disagreement, and reviewing them by another expert to determine the ground truth. Then, various performance metrics were calculated to evaluate the accuracy and effectiveness of the system for both the classification and detection tasks.

For the classification task of periapical lesions, the following metrics were used:

- Sensitivity = TP / (TP + FN): the proportion of actual positive cases that were correctly classified as positive.
- Specificity = TN / (TN + FP): the proportion of actual negative cases that were correctly classified as negative.
- Accuracy = (TP + TN) / (TP + TN + FP + FN): the proportion of all cases that were correctly classified.
- Precision = TP / (TP + FP): the proportion of true positive cases among all positive predictions.
- F1 score = 2 * (precision * sensitivity) / (precision + sensitivity): the harmonic mean of precision and sensitivity.

For the detection task of periapical lesions, the following metrics were used:

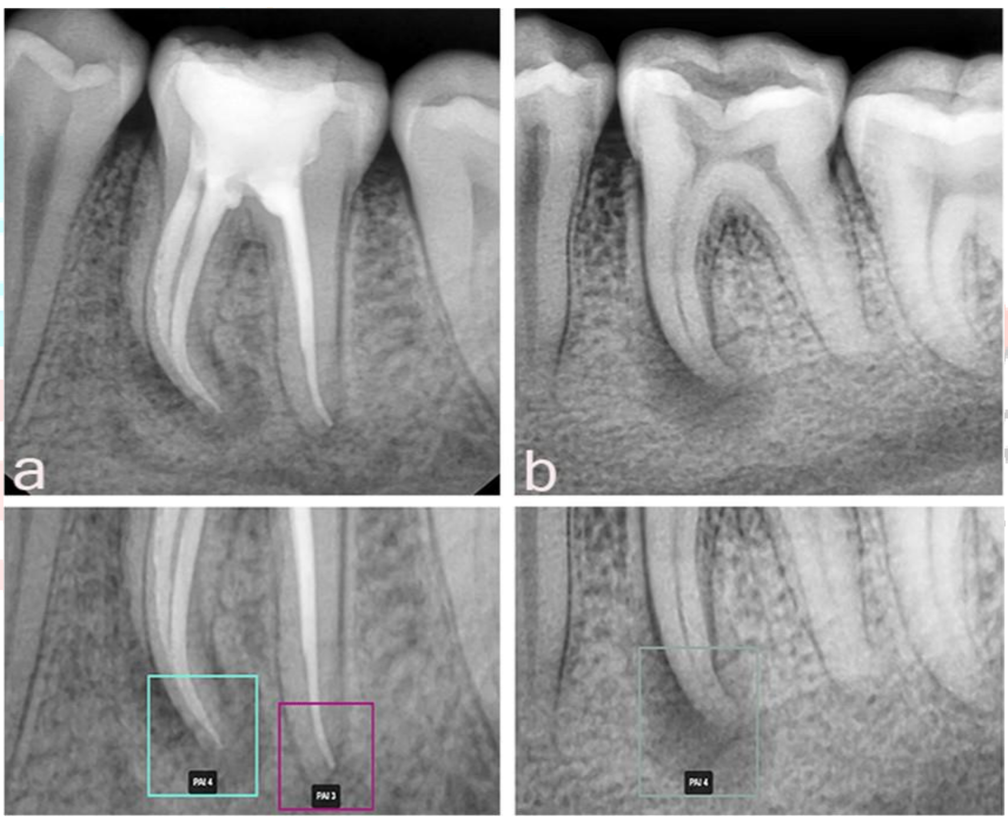
- Sensitivity = TP / (TP + FN): the proportion of actual lesions that were correctly detected.
- Specificity = TN / (TN + FP): the proportion of actual non-lesions that were correctly detected.
- Accuracy = (TP + TN) / (TP + TN + FP + FN): the proportion of all cases that were correctly detected.
- Precision = TP / (TP + FP): the proportion of true positive detections among all positive detections.
- F1 score = 2 * (precision * sensitivity) / (precision + sensitivity): the harmonic mean of precision and sensitivity.

In both tasks, TP represents the number of true positive cases (correctly classified or detected), FP represents the number of false positive cases (incorrectly classified or detected), FN represents the number of false negative cases (missed cases), and TN represents the number of true negative cases (correctly identified as negative). The metrics were used to evaluate the performance of both the system and the expert.

Results of periapical lesion detection

	System	**Expert**
True-positives		
False-negatives		
False-positives		
Precision		
Sensitivity		

Results:



Conclusion:

The use of machine learning techniques such as Convolutional Neural Networks (CNNs) has the potential to significantly improve the accuracy and efficiency of the diagnosis of periapical lesions. Our review of the methodologies used in this field highlights the importance of standardized data collection and preprocessing, thoughtful design of CNN architectures, and rigorous training and evaluation procedures.

The results of studies using CNNs for the classification and detection of periapical lesions have been promising, with high levels of accuracy and sensitivity demonstrated. However, there is still much work to be done in this field, particularly in the development of larger and more diverse datasets, as well as the refinement of CNN architectures to improve their performance.

Overall, the implications of using machine learning in the diagnosis of periapical lesions are significant, with the potential to improve patient outcomes and reduce the need for invasive diagnostic procedures. We encourage further research in this field, particularly in the development of standardized approaches to data collection and evaluation, to continue to advance the field and improve the quality of care for patients.

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