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Application of Deep Learning on Large-Scale Dental Imaging for Automated Diagnosis and Treatment Planning in Orthodontics and General Dentistry

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ABSTRACT

Dental imaging plays an important role in automated diagnosis, treatment planning, and clinical decision-making in orthodontics and general dentistry. Early and accurate identification of dental abnormalities from radiographic images can assist dentists in detecting pathological conditions, evaluating anatomical structures, and supporting effective treatment strategies. This study aims to apply deep learning on large-scale dental imaging for automated diagnosis and treatment planning support in orthodontics and general dentistry. For this research, a large dental radiographic image dataset was used, containing training, validation, and testing image samples with multiple dental conditions and anatomical categories. The proposed framework applied deep learning-based feature extraction, K-means pseudo-label clustering, and supervised classification models to classify dental image patterns into four cluster-based diagnostic groups. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, precision–recall curve, training-validation accuracy and loss curves, and LIME-based explainable artificial intelligence analysis. The results show that the proposed model achieved strong classification performance with an overall accuracy of 99.62% on 1,580 test images. The confusion matrix showed that most predictions were correctly classified across all four clusters, while ROC and precision–recall curves demonstrated excellent discriminative capability. The LIME visualization further indicated that the model focused on clinically meaningful dental and maxillofacial regions during prediction. The findings suggest that deep learning-based dental image analysis can support automated diagnosis, improve diagnostic efficiency, and contribute to preliminary treatment planning in orthodontics and general dentistry.

INTRODUCTION

Dental imaging is essential for diagnosis, treatment planning, and clinical decision-making in orthodontics and general dentistry. Radiographic images help dentists evaluate teeth, jawbone, dental caries, periodontal conditions, dental implants, anatomical structures, and other oral abnormalities. However, manual interpretation of dental radiographs can be time-consuming and may vary depending on image quality, anatomical overlap, and the clinical experience of the dentist. Artificial intelligence and deep learning have created new opportunities for automated dental image analysis because these methods can learn complex radiographic patterns from image data and support classification, detection, segmentation, and diagnostic decision-making. Deep learning has already been widely applied in oral and maxillofacial radiology, where convolutional neural networks are commonly used for dental diagnosis, detection, classification, and segmentation tasks (Hwang *et al.*, 2019). Recent studies also show that deep learning is promising for diagnosing dental anomalies and diseases and can support better diagnosis and treatment planning in dentistry (Sivari *et al.*, 2023). In dental diagnostic imaging, deep learning-based classification, object detection, and segmentation techniques are increasingly used to identify lesions, anatomical structures, and radiographic findings from intraoral, panoramic, and CBCT images (Katsumata, 2023). Several studies have demonstrated the effectiveness of deep learning in specific dental applications. For example, deep learning has been used for early dental caries detection in bitewing radiographs and has been shown to improve clinicians' diagnostic performance(S. Lee *et al.*, 2021). AI-based dental X-ray analysis has also been applied for recognizing periodontitis and dental caries, showing strong potential for faster and more accurate identification of common oral diseases(I. D. S. Chen *et al.*, 2023). In addition, automated deep convolutional neural networks have been used to classify dental implant systems from radiographic images and have shown effective performance compared with dental professionals (J.-H. Lee *et al.*, 2020). Deep learning has also been applied to dental treatment quality evaluation, where automated dental image analysis supported clinical decision-making using periapical radiographs(Yang *et al.*, 2018). Although previous studies have shown promising results, many existing systems focus on single disease detection or specific dental imaging tasks. Limited research has combined large-scale dental imaging,

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pseudo-label clustering, supervised classification, and explainable artificial intelligence for automated diagnosis and treatment-planning support. Therefore, this study applies deep learning-based feature extraction, KMeans pseudo-label clustering, supervised classification, and LIME-based explainability to classify dental radiographic images into meaningful cluster-based groups. The purpose of this study is to support automated diagnosis, improve diagnostic efficiency, and assist preliminary treatment-planning decisions in orthodontics and general dentistry.

LITERATURE REVIEW

Recent Developments in Deep Learning-Based Dental Imaging

Recent developments in deep learning have significantly improved dental image analysis by supporting automated diagnosis, disease screening, classification, and treatment-planning decisions. Deep learning models have been applied to oral photographs for gingivitis screening and localization, showing their usefulness for early dental disease detection and public oral health support(W. Li *et al.*, 2021). AI-enabled dental care has also expanded into oral radiology, orthodontics, maxillofacial surgery, periodontal disease management, and treatment planning, making dentistry more data-driven and precise (Yang *et al.*, 2018). However, model generalizability remains an important concern, as dental image models may perform differently across clinical centers and populations(Krois *et al.*, 2021). Recent studies also show that deep learning can detect and classify dental caries in CBCT images with high accuracy, supporting its role in automated diagnosis and clinical decision support (Esmaeilyfard *et al.*, 2024). Therefore, deep learning-based dental imaging has strong potential to improve automated diagnosis and preliminary treatment planning in orthodontics and general dentistry.

Theoretical and Practical Foundations of Automated Dental Diagnosis

Automated dental diagnosis is mainly based on deep learning, image classification, object detection, segmentation, and three-dimensional image analysis. In orthodontics, AI-based 3D systems can classify malocclusion from intraoral scans and support real-time diagnosis and treatment planning (H. J. Lee *et al.*, 2026). Similarly, 3D surface imaging with AI improves dental diagnostics by providing accurate, non-invasive, and patient-specific visual information for orthodontics, maxillofacial surgery, and clinical planning (Manjunatha *et al.*, 2024). Deep learning also supports digital dentistry by automatically segmenting teeth and gingiva from intraoral scans, which is important for orthodontic simulation, implant planning, and treatment design (Hao *et al.*, 2022). In radiographic diagnosis, object detection models such as Faster R-CNN can detect and number teeth in periapical films, reducing manual workload and improving diagnostic efficiency (H. Chen *et al.*, 2019). Therefore, the theoretical and practical foundation of this study is based on using AI-driven feature extraction, clustering, classification, and explain ability to support automated diagnosis and treatment-planning decisions in dental imaging.

Challenges in Deep Learning-Based Dental Image Analysis

Deep learning-based dental image analysis has strong potential for automated diagnosis and treatment planning, but several challenges still limit its clinical use. One major challenge is dataset bias, because AI models trained on limited or non-diverse data may not perform equally well across different populations and clinical settings (Sum, 2025). In dental radiology, traditional images may contain overlap, distortion, poor contrast, and anatomical complexity, which can affect accurate feature extraction and model prediction(Ali *et al.*, 2025). AI-based tele dentistry also faces challenges related to infrastructure, data privacy, clinical readiness, and integration with existing dental practice systems (Kaushik & Rapaka, 2025). Recent diagnostic studies further show that some AI tools may perform well for specific conditions, such as impacted third molars, but still have limited sensitivity for other impacted teeth, meaning human expert review remains necessary (Makrygiannakis, 2026). Therefore, deep learning models in dental imaging require diverse datasets, external validation, explainable decision-making, and careful clinical supervision before being fully adopted in orthodontics and general dentistry.

Limitations of Current Dental Imaging and Treatment-Planning Research

Current dental imaging and treatment-planning research has shown strong progress, but several limitations remain. Many CT and CBCT segmentation studies still face challenges related to small test datasets, risk of bias, and limited real-world generalizability (Dot *et al.*, 2024). In orthodontic AI systems, automated malocclusion classification has improved, but many models still need broader validation and integration with multimodal data for complete clinical diagnosis (Kavousinejad *et al.*, 2026). Similarly, 3D intraoral scan-based tooth segmentation and landmark localization can support orthodontic treatment planning, but performance may be affected by abnormal tooth shapes, missing teeth, and incomplete scan data(Wu *et al.*, 2022). In aesthetic dentistry, AI improves smile design, prosthetic planning, and outcome prediction, but issues such as data quality, privacy, bias, interpretability, and implementation cost remain important concerns (Ba-Zar *et al.*, 2025). CBCT-based AI models also require high-quality labeled data, while complex oral anatomy and lesion variation make automated segmentation difficult (Zheng *et al.*, 2021). Therefore, current research needs more diverse datasets, external validation, explainable models, and expert clinical supervision before deep learning-based dental imaging systems can be widely adopted in orthodontics and general dentistry.

Research Gap

Although deep learning has been increasingly used in medical and dental image analysis, limited studies have focused on combining large-scale dental radiographic imaging, pseudo-label clustering, classification, and explainable AI for automated diagnosis and treatment-planning support. Existing studies mainly focus on specific dental disease detection, while fewer studies organize dental image patterns into cluster-based groups and explain model decisions using visual interpretation methods. Therefore, this study addresses this gap by applying deep learning-based feature extraction, KMeans pseudo-label clustering, supervised classification, and LIME explain ability for dental imaging analysis in orthodontics and general dentistry.

Research Questions

1. How can deep learning be used for dental radiographic image analysis?
2. How can dental images be grouped using KMeans pseudo-label clustering?
3. How well can the proposed model classify dental images into four cluster-based groups?
4. How can performance metrics evaluate the accuracy and reliability of the proposed model?
5. How can LIME explain which dental image regions influenced the model's prediction?

Research Objectives

1. The main objective of this study is to apply deep learning on large-scale dental imaging for automated diagnosis and treatment-planning support in orthodontics and general dentistry.
2. To use deep learning-based feature extraction for identifying meaningful patterns from dental radiographic images.
3. To apply KMeans pseudo-label clustering for grouping dental images into four cluster-based diagnostic categories.
4. To evaluate the classification performance of the proposed model using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, and precision–recall curve.
5. To use LIME-based explainable AI to interpret model predictions and identify clinically meaningful dental and maxillofacial image regions.

MATERIALS AND METHODS

Study Area

This study was conducted in the context of dental radiographic image analysis for automated diagnosis and treatment-planning support in orthodontics and general dentistry. Dental imaging plays an important role in identifying dental abnormalities, evaluating anatomical structures, detecting pathological conditions, and supporting clinical decision-making. The study focused on large-scale dental radiographic images and aimed to classify meaningful dental image patterns using deep learning-based feature extraction and classification techniques.

Study Design

This study followed a quantitative and deep learning-based research design. Dental radiographic images were processed using deep learning-based feature extraction, KMeans pseudo-label clustering, and supervised classification. The extracted image patterns were classified into four pseudo-label groups: cluster_0, cluster_1, cluster_2, and cluster_3.

Sample Size and Selection

A large-scale dental radiographic image dataset was used in this study. The dataset was divided into training, validation, and testing sets for model development and evaluation. The testing set contained 1,580 images, including 628 samples from cluster_0, 210 from cluster_1, 70 from cluster_2, and 672 from cluster_3.

Measures and Variables

The main input variable was dental radiographic image data. The output variable was the KMeans-generated pseudo-label group. The independent variables were the deep image features extracted from dental radiographs, while the dependent variable was the predicted cluster class.

Data Collection Procedure

The dental images were organized, resized, normalized, and prepared for model training and testing. After preprocessing, deep learning-based feature extraction was applied. KMeans clustering was then used to generate pseudo-labels, and these labels were used for supervised classification.

Research Tools and Techniques

Python-based deep learning and machine learning tools were used for image preprocessing, feature extraction, clustering, classification, and visualization. KMeans clustering was used for pseudo-label generation, PCA was used for cluster visualization, and LIME was applied for explainable AI analysis.

Data Analysis Techniques

Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, precision–recall curve, accuracy curve, loss curve, and LIME visualization. The proposed model achieved an overall accuracy of 99.62%, with 1,574 correct predictions out of 1,580 test images.

RESULTS AND DISCUSSIONS

Classification Performance of the Proposed Deep Learning Model

This study applied a deep learning-based dental image classification framework for automated diagnosis and treatment-planning support in orthodontics and general dentistry. The model used large-scale dental radiographic images and classified the extracted image patterns into four KMeans-derived pseudo-label groups: cluster_0, cluster_1, cluster_2, and cluster_3. The classification performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix, ROC curve, precision–recall curve, accuracy curve, loss curve, and LIME-based explainable artificial intelligence analysis.

The proposed model achieved strong overall classification performance on the test dataset. Although the classification report rounded the accuracy value to 1.00, the exact confusion matrix calculation showed 1574 correct predictions out of 1580 test images, resulting in an overall accuracy of 99.62%. This indicates that the proposed model was highly effective in identifying dental image patterns and classifying them into cluster-based diagnostic groups. The detailed classification performance is shown in Table 1.

Table 1: Classification Performance of the Proposed Model

Class	Precision	Recall	F1-score	Support
cluster_0	1.00	1.00	1.00	628
cluster_1	1.00	0.99	0.99	210
cluster_2	1.00	1.00	1.00	70
cluster_3	0.99	1.00	1.00	672
Accuracy			99.62%	1580
Macro Average	1.00	1.00	1.00	1580
Weighted Average	1.00	1.00	1.00	1580

The results show that the proposed deep learning model achieved excellent classification performance across all four pseudo-label groups. The cluster_0, cluster_2, and cluster_3 classes achieved almost perfect prediction results, while cluster_1 achieved slightly lower recall due to a small number of misclassified samples. Overall, the model demonstrated strong capability in learning meaningful radiographic image features from dental imaging data.

KMeans Pseudo-Label Cluster Visualization

Before applying supervised classification, the extracted dental radiographic image features were analyzed using KMeans clustering. This step was used to organize similar dental image patterns into pseudo-label groups. The PCA projection was then applied to visualize the distribution and separation of the generated clusters.

Fig. 1 shows the KMeans pseudo-label clusters visualized using PCA projection. The dental image features were

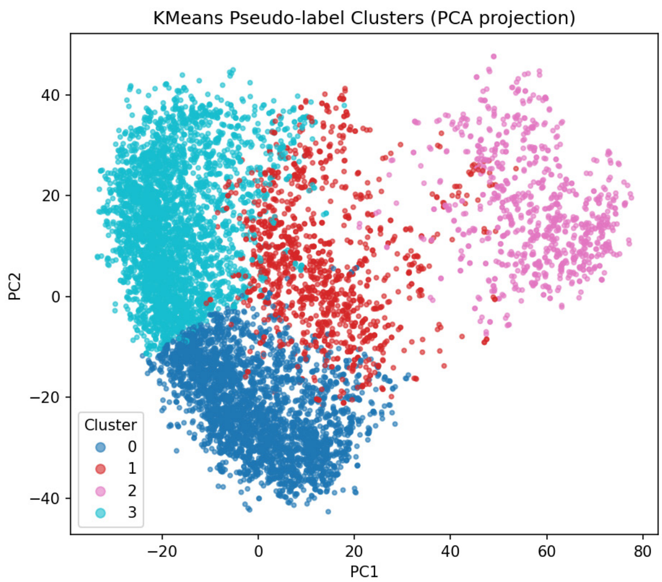

Figure 1: KMeans Pseudo-Label Clusters

grouped into four clusters, representing different radiographic pattern groups. The PCA projection shows that cluster_2 was more clearly separated from the other clusters, while cluster_0, cluster_1, and cluster_3 showed partial overlap in some regions. This indicates that several dental radiographic patterns had distinct feature distributions, while some patterns shared similar anatomical or visual characteristics.

The clustering result supports the use of pseudo-label-based classification for organizing large-scale dental images. Since dental radiographs often contain overlapping structures, such as teeth, jawbone, maxillary sinus, mandibular region, and dental restorations, partial overlap among clusters is expected. However, the overall cluster distribution suggests that the feature extraction process successfully captured important visual variations from the dental imaging dataset.

Confusion Matrix of the Proposed Model

The confusion matrix was used to evaluate how accurately the proposed deep learning model classified each dental image cluster. It provides a clear comparison between the actual KMeans pseudo-labels and the predicted labels generated by the model. This analysis helps identify both correctly classified and misclassified dental radiographic images.

Fig. 2 shows the confusion matrix of the proposed model against KMeans pseudo-labels. The model correctly classified 626 samples from cluster_0, 207 samples from

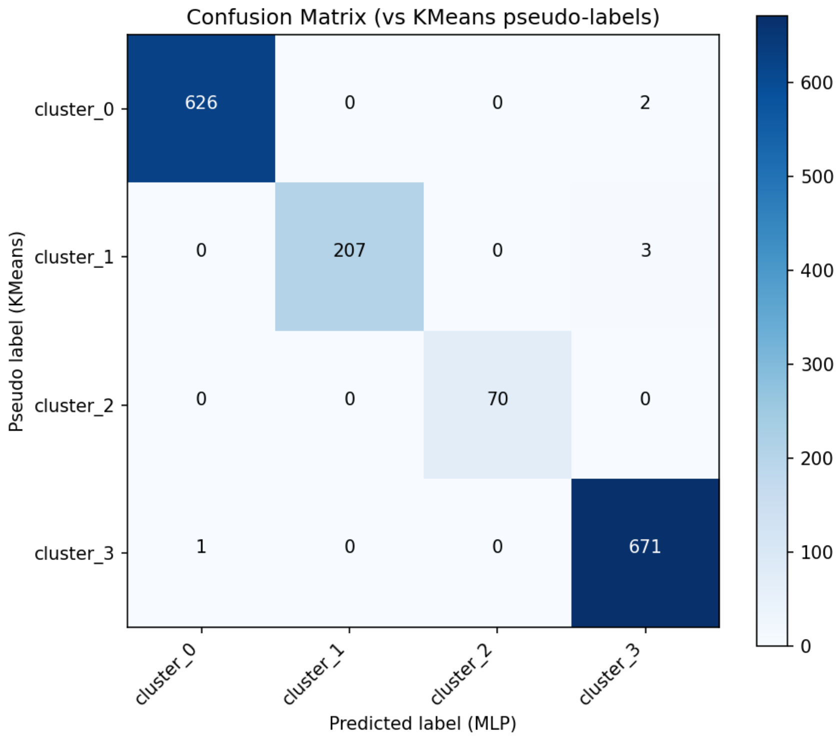

Figure 2: Confusion Matrix of the Proposed Deep Learning Model

cluster_1, 70 samples from cluster_2, and 671 samples from cluster_3. Only a small number of samples were misclassified across the four classes. Specifically, 2 samples from cluster_0 were predicted as cluster_3, 3 samples from cluster_1 were predicted as cluster_3, and 1 sample from cluster_3 was predicted as cluster_0.The diagonal values of the confusion matrix show that most predictions were correctly classified. Out of 1580 test images, 1574 images were correctly predicted, resulting in an exact accuracy of 99.62%. This indicates that the proposed deep learning model achieved highly reliable performance for classifying dental radiographic image patterns. The low number of misclassified samples further suggests that the model was able to distinguish between different cluster-based dental imaging groups with strong consistency.

Accuracy Curve of the Proposed Model

The ROC curve was used to examine the discriminative ability of the proposed model across the four pseudo-label classes. It shows how effectively the model separates one class from the remaining classes using a one-vs-rest classification approach. A higher curve near the top-left corner indicates stronger classification performance.

Fig. 3 presents the training and validation accuracy curves of the proposed model. The training accuracy increased rapidly during the initial epochs and remained close to 99% throughout the training process. The validation accuracy also remained consistently high, staying above 98% and reaching approximately 99% during later epochs. This indicates that the model learned meaningful dental image features and maintained strong generalization performance on validation data.

Loss Curve of the Proposed Model

The precision–recall curve was used to evaluate the reliability of the model in predicting each dental image cluster. This analysis is important because the dataset contains unequal class distributions across the pseudo-label groups. High precision and recall values indicate that the model can correctly identify dental image patterns while reducing false predictions.

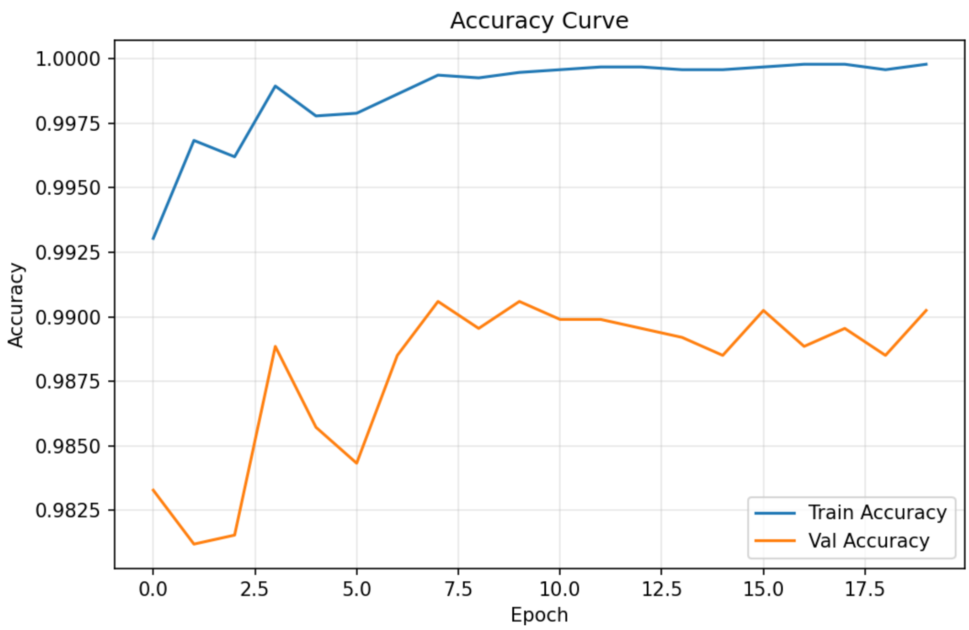

Figure 3: Training and Validation Accuracy Curve

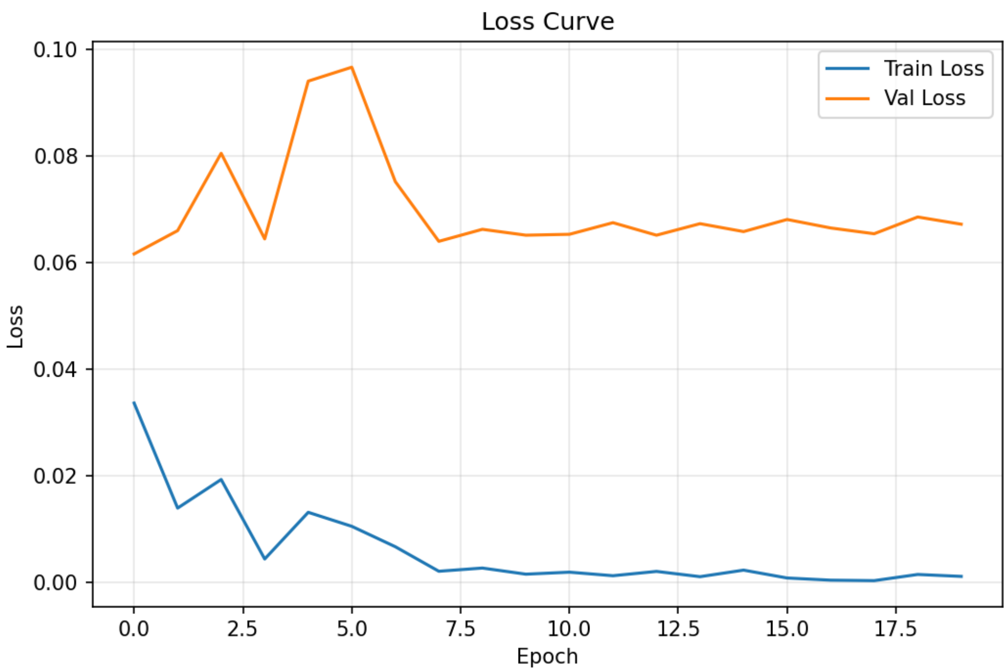

Figure 4: Training and Validation Loss Curve

Fig. 4 shows the training and validation loss curves of the proposed model. The training loss decreased gradually and remained very low after several epochs, indicating that the model successfully minimized classification error during training. The validation loss remained higher than the training loss but stayed relatively stable after the early training phase. This pattern suggests that the model learned strong discriminative features while maintaining stable validation performance.

Multi-Class ROC Curve of the Proposed Model

Explainable artificial intelligence was applied to understand the decision-making behavior of the proposed deep learning model. LIME visualization highlights the image regions that contributed most strongly to the model prediction. This helps verify whether the model focused on clinically meaningful dental and maxillofacial areas rather than irrelevant background regions.

Fig. 5 presents the one-vs-rest ROC curve for the four

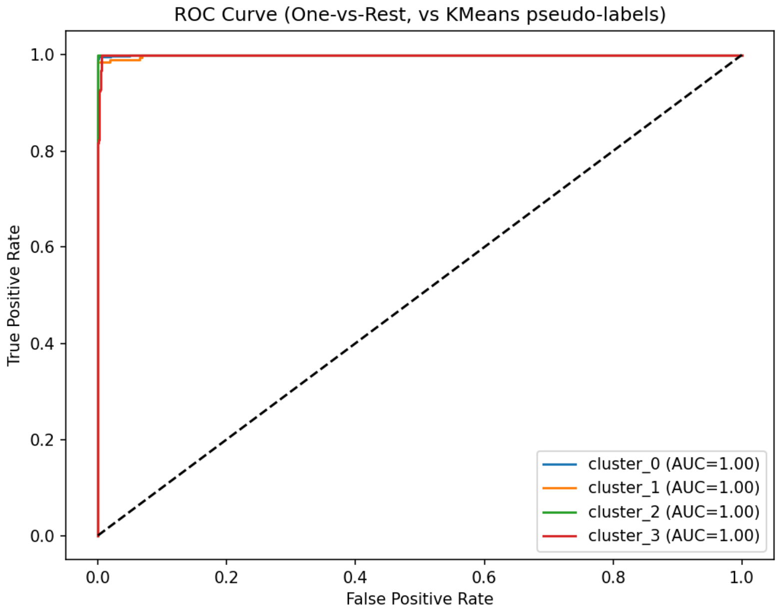

Figure 5: Multi-Class ROC Curve of the Proposed Model

KMeans pseudo-label classes. The ROC curve shows that the model achieved excellent discriminative capability across all four clusters. The AUC values for cluster_0, cluster_1, cluster_2, and cluster_3 were rounded to 1.00, indicating near-perfect separation between each class and the remaining classes.The ROC curve remained close to the top-left corner of the graph, which indicates a very high true positive rate and a very low false positive rate. These findings confirm that the proposed deep learning model was able to distinguish different dental image pattern groups with strong classification confidence. Therefore, the ROC analysis supports the effectiveness of the proposed model in automated dental image classification.

The overall results demonstrate that the proposed deep learning-based dental imaging framework achieved highly accurate classification performance across four pseudo-label groups. These findings suggest that deep learning can effectively support automated dental image analysis by identifying meaningful radiographic patterns. The proposed framework can contribute to automated diagnosis, clinical decision support, and preliminary treatment-planning assistance in orthodontics and general dentistry.

Discussion

This study applied deep learning on large-scale dental imaging for automated diagnosis and treatment-planning support in orthodontics and general dentistry. The proposed framework used deep learning-based feature extraction, KMeans pseudo-label clustering, supervised classification, and LIME-based explainable AI analysis. The model achieved strong classification performance with an overall accuracy of 99.62%, indicating that deep learning can effectively identify meaningful dental radiographic image patterns. This finding is consistent with recent evidence showing that AI and deep learning can improve diagnostic accuracy, treatment planning, and clinical decision-making in dental image-based diagnostics (Khattak *et al.*, 2025). The high performance of the proposed model also supports previous findings that deep learning models can classify different dental radiograph types with high accuracy and that explainable AI can help identify image regions consistent with expert reasoning (Cejudo *et al.*, 2021). In addition, the results are relevant to disease-specific dental image studies, as deep learning has shown high accuracy in classifying periodontitis stages from dental images and may reduce professional workload while improving classification consistency(X. Li *et al.*, 2023). Similarly, deep learning has shown strong performance in identifying and classifying dental implant systems from radiographic images, supporting its potential as a clinical decision-support tool in dentistry (Chaurasia *et al.*, 2024) . The LIME visualization in this study further showed that the model focused on clinically meaningful dental and maxillofacial regions rather than irrelevant background areas. However, as the study used KMeans-generated pseudo-labels, future research should validate the proposed framework using expert-labeled clinical datasets and independent external dental imaging data. Overall, the findings suggest that deep learning-based dental image analysis can support automated diagnosis, improve diagnostic efficiency, and assist preliminary treatment-planning decisions in orthodontics and general dentistry.

Findings

1. The proposed deep learning model successfully classified dental radiographic images into four KMeans-based pseudo-label groups.

2. KMeans clustering helped organize large-scale dental image patterns into meaningful cluster-based categories.

3. The model achieved strong classification performance with an overall accuracy of 99.62% on 1,580 test images.

4. The confusion matrix, ROC curve, and precision–recall curve showed that the model had high reliability and strong discriminative ability across all four clusters.

5. LIME-based explainable AI analysis showed that the model focused on clinically meaningful dental and maxillofacial regions during prediction.

Recommendations

1. Deep learning-based dental image analysis should be used as an assistive tool to support automated diagnosis in orthodontics and general dentistry.

2. KMeans pseudo-label clustering can be applied to organize large dental imaging datasets when manual labeling is limited or unavailable.

3. Explainable AI methods such as LIME should be included to improve transparency and clinical trust in dental image classification models.

4. Future systems should combine deep learning classification with expert dental review to support more reliable treatment-planning decisions.

5. Larger and more diverse dental radiographic datasets should be used in future research to improve model generalization across different clinical settings.

Limitations

1. The study used KMeans-generated pseudo-labels instead of fully expert-annotated clinical labels, which may limit direct diagnostic interpretation.

2. The model was evaluated using the available dental imaging dataset, so external validation on independent clinical datasets is needed.

3. The study focused mainly on image classification and explainability; detailed disease-specific diagnosis and complete treatment-planning automation were not included.

CONCLUSION

This study applied deep learning on large-scale dental imaging for automated diagnosis and treatment-planning support in orthodontics and general dentistry. The proposed framework used deep learning-based feature extraction, KMeans pseudo-label clustering, supervised classification, and LIME-based explainable AI analysis. The model classified dental radiographic images into four cluster-based groups and achieved an overall accuracy of 99.62% on 1,580 test images. The confusion matrix, ROC curve, and precision–recall curve confirmed strong classification performance, while LIME visualization showed that the model focused on clinically meaningful dental and maxillofacial regions during prediction. Therefore, this study concludes that deep learning-based dental image analysis can support automated diagnosis, improve diagnostic efficiency, and assist preliminary treatment-planning decisions in orthodontics and general dentistry. In future work, the proposed model should be validated using expert-labeled clinical datasets and independent external dental imaging data. Future studies may also include disease-specific classification, segmentation-based localization, and integration with clinical decision-support systems to improve real-world diagnostic reliability and treatment-planning applications.

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