Keywords
Machine learning, Dental radiographs, Tooth classification, Panoramic imaging, Oral surgery

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Machine Learning and Deep Learning Applications in Oral Surgery and Dental Sciences

Abstract
Objectives; Cigarette smoking is a clinically relevant risk factor in dentistry because it may influence systemic metabolism, tissue healing,
Artificial intelligence has growing relevance in oral surgery and dental sciences, particularly for radiographic interpretation, tooth localization, and image-based decision support. Interpretable machine learning approaches may provide practical value where structured anatomical features are available from annotated dental images. The present study evaluated the application of machine learning for automated tooth classification and anatomical analysis using annotated panoramic dental radiographs. A secondary dataset of annotated panoramic dental radiographs was analyzed. Pascal VOC annotation files were processed to extract tooth-class labels, image dimensions, bounding-box coordinates, and derived geometric features. Descriptive and morphological analyses were performed, followed by supervised multiclass classification using a Random Forest model. Model performance was evaluated using accuracy, precision, recall, F1-score, confusion matrix analysis, feature-importance assessment, and five-fold cross-validation. A total of 14,227 annotated tooth regions from 585 radiographs and 16 tooth classes were analyzed. The model achieved a test-set accuracy of 90.62%, with weighted precision, recall, and F1-score values above 90%. Five-fold cross-validation showed stable performance, with a mean accuracy of 90.33% and a low standard deviation of 0.0032. Feature-importance analysis indicated that horizontal tooth-region coordinates were the strongest predictors of classification performance. The findings support the use of lightweight and interpretable machine learning models for dental image analysis, radiographic assessment, and decision-support applications in oral surgery and dental sciences.

1. INTRODUCTION

Artificial Intelligence (AI) is revolutionizing healthcare, with its ability to process large volumes of clinical data, assist in diagnoses, and streamline treatment processes. Among the several subfields of AI, two of the important fields are machine learning (ML) and deep learning (DL), which have been really helpful in medical imaging, disease prediction and automated healthcare analysis [1]. With the growing influence of AI on radiological processes, intelligent systems have been rapidly evolving to identify intricate anatomical patterns and aid in clinical interpretation.

As computational image analysis has been developed, the applications of AI based image analysis in healthcare imaging sciences have been enhanced even further [2]. There has been a significant digital transformation in dental and oral healthcare, with the use of digital radiographic systems now being widespread. A panoramic dental radiograph is useful for the overall overview of the maxillofacial structures and is frequently used in oral surgery, oral implant planning, orthodontics and diagnostic dentistry [3]. With the increasing accessibility of digital dental imaging, opportunities have arisen to leverage AI techniques for image analysis that can support clinicians in image interpretation and anatomical localization. The advent of the latest

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technologies in oral healthcare shows that AI brings the promise of enhancing the accuracy and speed of diagnostics, decreasing the clinical burden and workload, and facilitating personalized treatment plans in the field of dentistry [4].

In the past decade, the use of AI in oral and maxillofacial surgery has increased significantly. Intelligent imaging systems are explored for surgical planning, interpretation of radiographs, detection of lesions and evaluation of anatomy. AI technologies can help clinicians determine which anatomical structures are relevant to the patient from a complex radiographic image, and might help streamline preoperative assessment processes [5]. Digital imaging and the computer-assisted system have become a part of implant dentistry workflows in guided implant placement and the evaluation of anatomical areas [6]. AI has been a subject of many studies in dental image analysis due to the complexity of anatomical information in dental images that may be challenging to process manually. The use of automated image-analysis systems may help standardize and minimize interobserver variability in diagnosis for teeth. AI-powered dental image analysis shows potential for accurate tooth identification and lesion detection, as well as for interpreting radiographs, in systematic studies [7]. In panoramic dental imaging, the deep learning models have demonstrated their effectiveness, especially in the detection and localization of oral structures [8].

Previous studies have explored a broad range of ML and DL techniques for dental and maxillofacial image analysis. CNNs are able to learn hierarchical visual features directly from the image data and have been extensively applied in image classification, image segmentation and object detection in dental radiographs [9]. CNN-based methods are found to be effective in predicting dental X-ray images and the anatomical area of panoramic X-ray images [10]. The use of hybrid transfer-learning for tooth diagnosis and classification from orthopantomogram (panoramic) radiographs has also been explored, highlighting the increasing trend of AI-assisted dental image interpretation [11]. Since structured and quantitative clinical features can be analyzed in a predictive manner, Machine learning methodologies have been gaining significance in precision healthcare [12]. In the field of dental sciences, AI-based multi-class classification systems are being built to assist in the classification of diseases and to recognize anatomical structures automatically. In recent research, the feasibility of using AI in panoramic radiograph-based classification systems in partially edentulous patients and other dental diagnostic approaches has been proven [13]. All these advances suggest that intelligent dental image analysis and clinical decision-support systems have made significant strides.

Although there has been an increasing number of studies focused on AI in dentistry, the current literature has several limitations. Numerous studies are based on complex deep learning architectures, which are usually quite intensive to compute and need massive collections of images, powerful hardware, and long training time. Fewer studies have investigated lightweight, interpretable ML methods using features from dental radiographs, derived from structured annotations. Moreover, there has been little focus on the statistical morphological analysis and the combination with the multi-class machine learning classification based on features of anatomical localization obtained from annotated panoramic images. Most studies are limited to detection or segmentation problems, and few studies test for reproducibility and robustness using systematic cross-validation methods in a secondary annotated dental dataset.

In the present study, we studied the use of machine learning techniques in the field of oral surgery and dental science with the help of annotated panoramic dental radiographs. The study included automated tooth classification and anatomical analysis by extracting spatial and morphological features of the radiographic annotations. A Random Forest multiclass classification framework has been used to work out the predictive performances with the variables extracted from structured annotations. Additionally, statistical analysis, feature-importance evaluation, confusion-matrix analysis and cross-validation procedures were conducted to evaluate the robustness, interpretability and applicability of the model in the dental image analysis workflow.

2. Methodology

2.1 Research Design

This study used a descriptive secondary data analysis method with a quantitative approach to explore the use of machine learning techniques in oral surgery and dental sciences. To evaluate the potential for automated tooth classification, a supervised multiclass classification framework was designed by using annotated panoramic dental radiographs, anatomical and spatial information. Data preprocessing, extraction of annotations, Feature Engineering, Creation of machine learning models, Statistical analysis and validation of the model's performances were done.

2.2 Data Source

The data set used in this study was a publicly available data set of panoramic dental X-rays and annotation files [14]. The data set included multiple categories of teeth, with spatial localization information given as coordinates of the bounding boxes. Radiographic images were labelled with anatomical and positional information, and then quantitative anatomical and positional information were extracted for analysis using machine learning. The data set included training, validation, and test sets suitable for the supervised multiclass classification problem.

2.3 Data Preprocessing and Annotation Extraction

The pre-processed data is annotated with the target class labels. Each of the annotation files in Pascal VOC XML format was read, and the class label, image size and the BB coordinates for each tooth region were extracted for each image. Other geometric attributes, such as width, height, total area, and proportion of relative box-area, were also derived from the coordinates obtained. The resultant processed annotations were then structured in tabular format for performing statistical analysis and machine learning implementation. Records where data is missing were removed to ensure data consistency.

2.4 Exploratory and Statistical Analysis

Descriptive statistical analysis was conducted to assess the distribution and the morphological features of the dental structures annotated. The quantitative summary measures were used to compare class-wise annotation frequencies, composition of the dataset and spatial variation in the occurrence of tooth regions. The variation of tooth classes with spatial and anatomical relationships was further investigated using the dimensions of their enclosing boxes and the distribution of areas in different regions of the boxes. These analyses have been performed to discover discriminative anatomical patterns relevant to automatic tooth classification.

2.5 Feature Engineering

The variables of prediction were obtained from the coordinates and geometric characteristics of the extracted annotations. Spatial coordinates, dimensions of the bounding boxes, total area of the bounding boxes, and proportion of the relative area were selected as the features. These variables were considered as the location and shape of the tooth areas on panoramic X-rays. To minimize the scale variation and classification uniformity of the model training, numerical features were standardized before model development.

2.6 Machine Learning Model Development

The machine learning framework was used to implement a Random Forest multiclass classification model. The model was chosen for its strength with structured numerical data, for avoiding overfitting and for delivering interpretable estimates of feature importance. Stratified sampling was used to partition the data set into training and test sets to ensure proportional representation of the tooth classes. To minimize the bias of the classification process due to the uneven distribution of classes, multiple decision trees with the same class weighting were used in the Random Forest classifier.

2.7 Performance Evaluation

The performance of the machine learning model was assessed using accuracy, precision, recall, and F1 score. Two performance metrics were used to evaluate the overall multiclass classification performance: the weighted-average and macro-average. To assess the class-wise prediction behaviour, a confusion matrix was created, and the possible misclassification patterns between anatomically related tooth classes were observed. Spatial and morphological variables were further ranked using the feature-importance analysis to identify their relative importance for tooth classification. Five-fold stratified cross-validation was used to evaluate the stability and reproducibility of the model. The accuracy, precision, recall and F1 score metrics were averaged over all validation folds and standard deviations were computed.

3. RESULTS

3.1 Dataset Characteristics and Annotation Distribution

The characteristics of the data sets and how the annotations are distributed. The 14,227 annotated tooth regions were obtained from 585 panoramic dental radiographs with 16 different tooth classes. The data was split into training, testing and validation sets of 10,019, 2,937 and 1,271 annotations. The average width and height of the bounding boxes were 33.77 and 134.14 pixels, respectively, and 4504.06 pixels^2 was the average area of the bounding boxes. The results suggest that there is considerable anatomical variation among all of the dental structures labelled. The overall characteristics of the dataset and the statistics of the annotations used for machine learning analysis are shown in Table 1.

Table 1. Dataset Characteristics

Characteristic	Value
Total annotations	14,227
Total images	585
Number of tooth classes	16
Training annotations	10,019
Testing annotations	2,937
Validation annotations	1,271
Mean bounding box width	33.77
Mean bounding box height	134.14
Mean bounding box area	4504.06
Mean relative bounding box area	0.011

A class-wise distribution of the annotations showed a relatively even distribution of the major tooth categories, but there were some moderate differences in annotation frequencies among classes. The highest number of annotations was in the RMU and LMU categories, while the lowest number was in the RCU and LCU categories. Figure 1 shows the distribution of the number of annotated tooth classes over the data set.

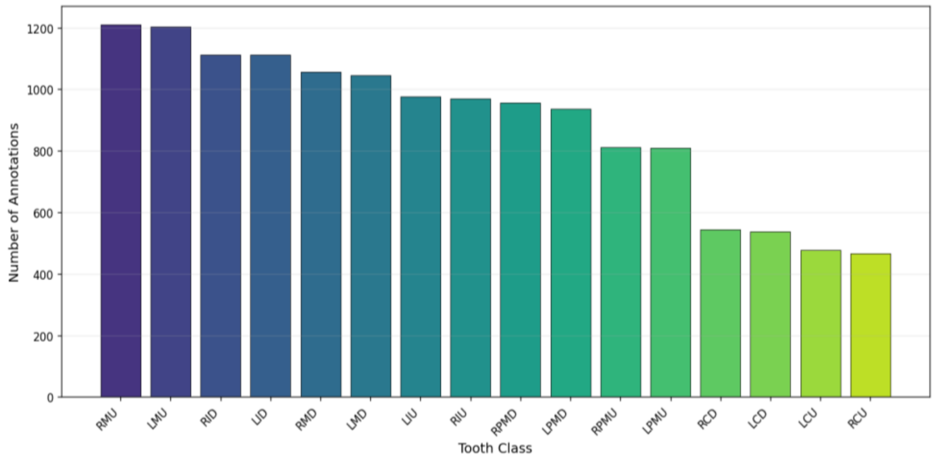

Figure 1. Distribution of Annotated Tooth Classes

The data split composition also showed that about 70.4% of the data were assigned to train the model, while testing and validation data subsets were 20.6% and 8.9%, respectively. The proportional distribution allowed for adequate data to be available for supervised learning and independent model evaluations. The split composition of the dataset is given in Figure 2.

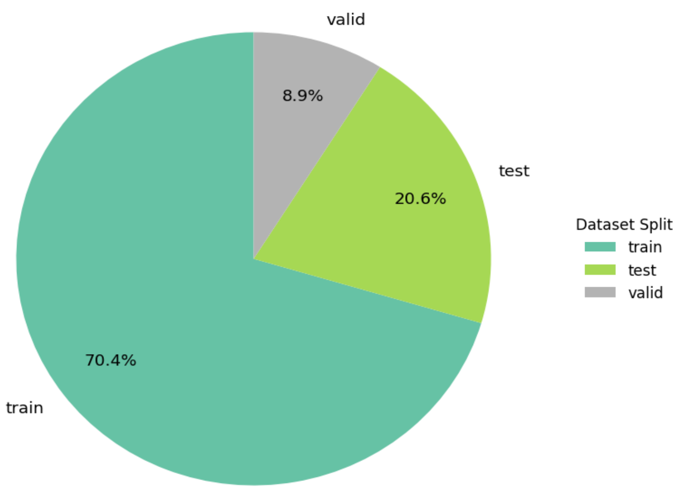

Figure 2. Dataset Split Composition

3.2 Morphological Analysis of Tooth Regions

A significant morphological difference was found among the 16 classes annotated in the tooth region. The mean areas of the bounding boxes of RMD and LMD were the highest with 7046.58 pixels² and 6573.41 pixels², respectively. By contrast, the mean bounding-box areas for both RID and LID were less than 2800 pixels², indicating the smallest average anatomical areas. The results showed a variation that indicates that the different tooth classes have different anatomic dimensions and spatial characteristics in panoramic dental images. This morphological variation can help with discriminatory information for the process of tooth classification using machine learning. The frequencies and morphological statistics for the classes of the annotations are summarized in Table 2. Figure 3 shows the spatial distribution of average areas of tooth regions.

Table 2. Class-Wise Annotation and Morphology Summary

Tooth Class	Annotation Count	Mean Box Width	Mean Box Height	Mean Box Area	Standard Deviation of Box Area	Percentage (%)
RMU	1210	39.34	129.06	5066.41	1133.23	8.50
LMU	1204	37.05	127.35	4721.02	1051.60	8.46
RID	1113	22.26	121.28	2707.79	753.89	7.82
LID	1113	21.80	120.04	2621.22	732.57	7.82
RMD	1057	57.23	121.95	7046.58	1906.36	7.43
LMD	1045	53.02	122.76	6573.41	1821.20	7.35

LIU	977	26.93	148.12	4014.41	989.52	6.87
RIU	969	27.45	149.89	4142.25	1021.19	6.81
RPMD	957	35.32	135.60	4801.17	1388.33	6.73
LPMD	936	33.54	135.11	4536.15	1261.65	6.58
RPMU	812	29.71	141.42	4201.43	967.72	5.71
LPMU	809	28.67	140.96	4058.90	962.40	5.69
RCD	544	29.83	140.51	4197.22	1162.72	3.82
LCD	537	29.04	138.85	4049.93	1149.61	3.77
LCU	477	27.25	154.31	4222.89	925.32	3.35
RCU	467	28.11	157.40	4437.05	961.42	3.28

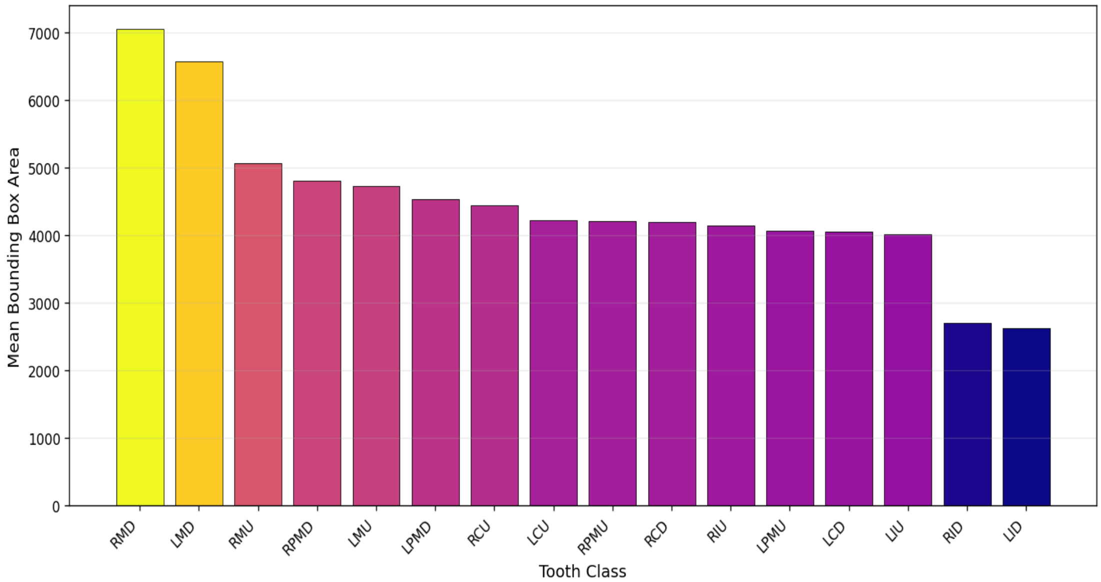

Figure 3. Average Tooth Region Area by Class

3.3 Machine Learning Classification Performance

The framework of machine learning has achieved good multiclass prediction performance for automated tooth classification. The Random Forest classifier has been able to obtain a test set accuracy of 90.62% and weighted precision, recall, and F1-score values of more than 90%. The macro-average metrics were marginally lower than the weighted-average metrics, which showed some degree of performance difference among different tooth classes. Five-fold cross-validation also showed similar stability of the model with a mean accuracy of 90.33%, and very low standard deviations of all performance measures. The low variance values suggest good model reproducibility and little tendency for overfitting. The overall classification and cross-validation performance metrics are summarised in Table 3.

Table 3. Model Performance and Cross-Validation Summary

Metric Group	Accuracy	Precision	Recall	F1 Score	Support
Test set accuracy	0.9062	N/A	N/A	N/A	2846
Macro average	N/A	0.8926	0.8925	0.8920	2846
Weighted average	N/A	0.9072	0.9062	0.9062	2846
Cross-validation mean	0.9033	0.9034	0.9033	0.9030	N/A
Cross-validation standard deviation	0.0032	0.0028	0.0032	0.0031	N/A

In the feature importance analysis, the horizontal spatial coordinates were the most important predictors of the tooth classification. The left and right boundary coordinate features contributed greatly compared to image dimension features, which shows that the anatomical position has a significant effect on automated dental structure recognition. The contribution of individual predictive features is shown in Figure 4.

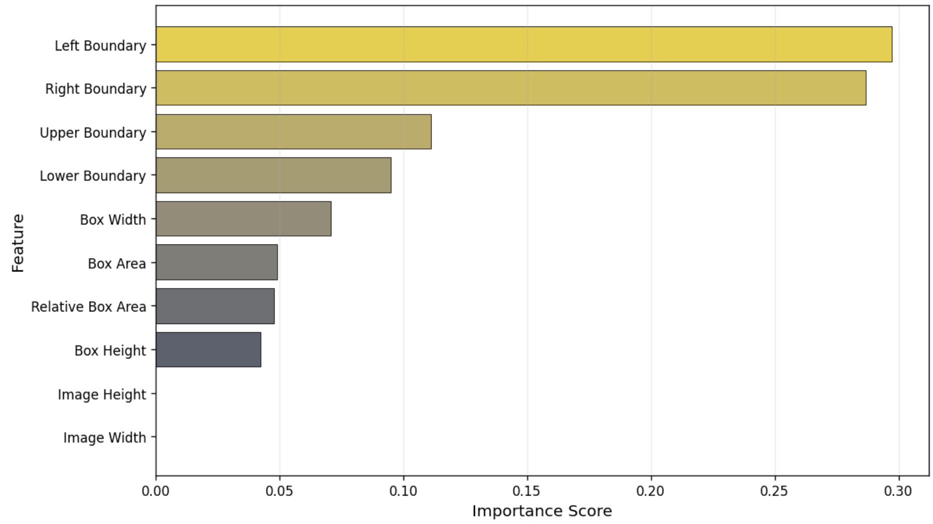

Figure 4. Feature Importance in Tooth-Class Prediction

It was observed that most of the tooth categories were classified with high accuracy as the diagonal dominance of the normalized confusion matrix was noticed. The low misclassification rates off the diagonal were most commonly observed between neighbouring tooth classes on the anatomy, reflecting morphological similarity between panoramic radiograph images. In Figure 5 the normalized confusion matrix for the prediction of the tooth classes is displayed.

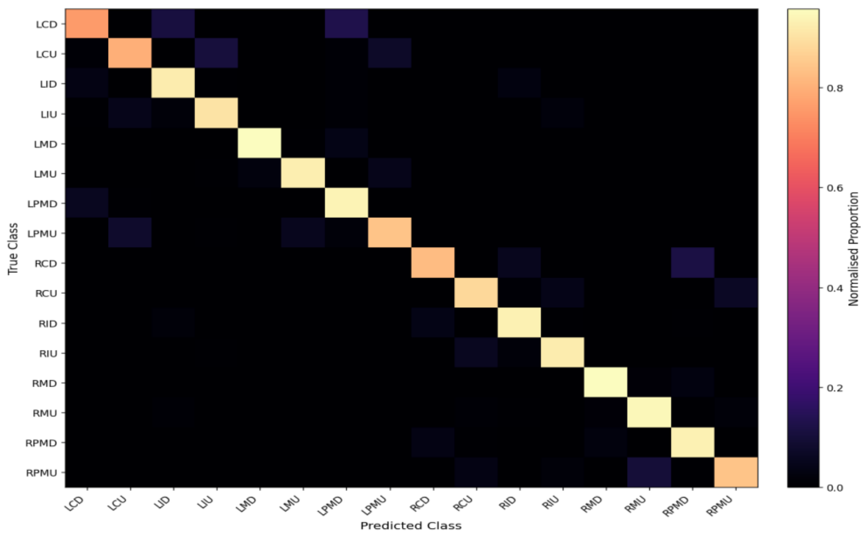

Figure 5. Normalized Confusion Matrix for Tooth-Class Prediction

The cross validation performance curves did not fluctuate much and were very similar with little variability in the accuracy, precision, recall and F1 score. These results also confirm the strength and overall applicability of the proposed machine learning solution for analysing dental images. Five-fold cross-validation performance results are given in Figure 6.

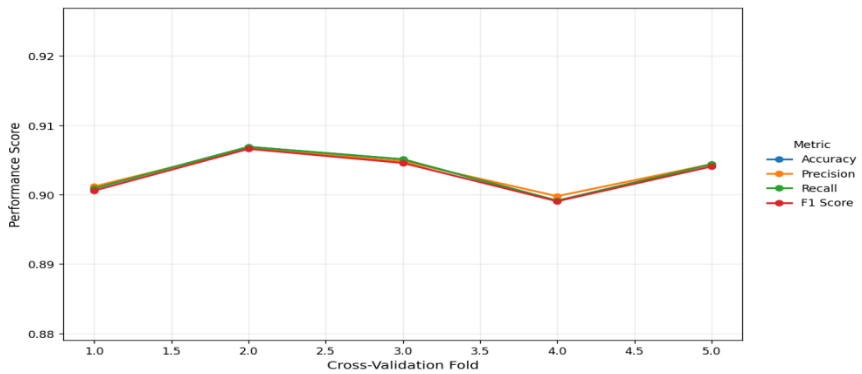

Figure 6. Five-Fold Cross-Validation Performance

4. DISCUSSION

The results indicate that the spatial and morphological features that are obtained from the annotated images are beneficial for the accurate automated tooth classification from the panoramic dental images. A total of 14,227 annotated tooth regions (from 16 different tooth classes) were included in this data set, which was sufficiently structured to be analyzed in a multiclass approach. Overall distribution of the categories of teeth was fairly uniform with some variation between the more frequently observed categories (RMU, LMU) and the less frequently observed categories (RCU, LCU), contributing to the robustness of the model training process. Random Forest classifier gave the test set accuracy of 90.62% with weighted precision, recall and F1 score greater than 90%. Overall, this suggests that the model was successful in categorizing the different types of teeth. The slightly lower macro-average scores indicate that there was some residual class-wise variability, likely due to classes with fewer annotations or with more similar anatomy. The high diagonal elements in the normalized confusion matrix also suggest a good capacity of the model to recognize most of the tooth classes with good accuracy, with relatively few off-diagonal elements showing that the majority of misclassifications were made between classes that are closely related or adjacent anatomical regions.

The results of the feature importance have interpretive value. The most important contributors to classification were horizontal boundary coordinates, vertical boundary coordinates and bounding box dimensions. This indicates that the positioning of the tooth in the panoramic image was a significant factor in the prediction of class. The fact that image width and height had a negligible effect was to be expected since the images were standardized to a fixed resolution. The average area of the bounding-box of the tooth region was also found to vary as per the class, with RMD and LMD having the highest average bounding box area and RID and LID having the lowest average bounding box area. These patterns showed that spatial location and regional morphology were both beneficial to achieve automated dental structure recognition. The 5-fold cross-validation was performed to check the stability of the model. All the metrics, including mean accuracy, precision, recall and F1 scores, were close to 90% with very low standard deviations across folds. This uniformity is indicative of the fact that the model was not reliant on a particular random train-test split and that its performance was repeatable over the various splits of the data.

It is consistent with recent studies on dental AI that have shown the models can effectively detect and classify tooth structures. Hence, spatial location is crucial for the interpretation in dental images. Li et al. demonstrated the efficacy of the detection of the position of the tooth in dental radiography using YOLOv4 and CNN [15]. Similarly, a few object detection-based models have been developed for the detection and classification of different dental abnormalities and teeth type detection using transformer-based models of YOLO, which has increased its applications in dental diagnostics [16]. The capability to classify dental diseases recognized by using orthopantomography-based deep learning studies is also high. Almalki et al. evaluated deep learning models for dental disease classification via OPG images, further highlighting the role of panoramic images in AI-assisted diagnosis of dental conditions [17]. Yoon et al. also proved that AI can help in caries detection and tooth number detection simultaneously, which highlights the need for an automated tooth detection in clinical image workflow [18].

Comparative studies on object detection have highlighted that the performance of models depends on the complexity of the task, the anatomical target and the imaging characteristics. To compare the detection performance of Faster R-CNN, YOLO and SSD for TMAs in panoramic images, Vilcapoma et al. demonstrated that varying detection architectures might provide different advantages based on the clinical task [19]. The applications of multi-regional deep learning methods for detecting dental restorations and prostheses in panoramic radiographs have also been proven to be useful in complex dental images [20]. The current method is unlike many deep learning papers, where the model is trained directly on the pixels in an image, and is instead based on features extracted from structured annotations. However, its performance is consistent with the general results reported in the literature regarding the discriminatory power of tooth position, regional anatomy and radiographic structure. The clinical relevance of automated tooth localization and classification is also supported by recent work that uses YOLOv10 in the detection and numbering of teeth in mixed dentition [21]. Panoramic Radiographic AI has also been used as a caries detection tool under fixed prostheses, which further suggests that dental radiographic AI can be used for anatomical and disease applications [22].

The outcomes apply to oral surgery and dental sciences. Automated tooth classification and localization could be used for the screening of panoramic dental images, anatomical analysis, and preoperative planning and for interpreting panoramic dental images in a structured manner. In oral surgery, it is crucial to identify the position of a tooth for the extraction planning, assessment of impacted teeth, evaluation of implants, and for the surgical navigation support. An interpretable machine learning model is also of importance. The model is more transparent than pure black-box approaches, as the contribution of the spatial and morphological variables can be examined using feature-importance analysis. This interpretability may be useful in clinical and educational applications when a clinician may want to know why a model has classified something as such. The lightweight nature of the approach could also prove useful for applications where computational resources are constrained or when a quick preliminary analysis is needed.

There are some limitations to point out. A secondary dataset was used, which meant that the image acquisition conditions and annotation procedures could not be controlled. Tooth-region classification was based on the features derived from the annotation and not on the raw image pixels, which means that the results are for the model after the annotation is extracted from the image, not an end-to-end radiograph diagnosis. No external validation on an independent dataset was done.

In the future, the framework should be tested with larger and more diverse data sets of dental radiographs. For possibly even better performance, but maintaining interpretability, structured feature-based models and deep learning architectures can be intersected. Other research could include clinically-specific oral surgery outcomes, including localization of impacted teeth, assessment of implant site and prediction of surgical risk.

5. CONCLUSION

The results showed that machine learning had great promise in the automatic classification and analysis of teeth in panoramic dental radiograph images. The predictive performance of the Random Forest model was good with a test-set accuracy of 90.62% and weighted precision, recall and F1 score values of over 90%. Results of cross-validation also showed good stability of the model with minimal fluctuations for each fold. The spatial boundary features were the most relevant features for the classification, meaning the anatomical location is important for dental image interpretation. The results show that machine learning techniques based on interpretability can be used in oral surgery and dental sciences for the localization of teeth, oral X-ray image evaluation, and to support structured decision making. While the analysis was conducted on features derived from annotation data from a secondary dataset, the results suggest that lightweight models can be used to give reliable and clinically relevant insights. Future studies are needed to confirm the framework using larger datasets from independent sources and to combine feature-based learning with deep learning techniques for more applications in the diagnosis and surgery.

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