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Artificial Intelligence-Driven Dental Age Estimation in Panoramic Radiographs via the Demirjian Method

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Abstract:

Objective(s): This research aimed to design and implement an artificial intelligence (AI) model for dental age estimation in panoramic radiographs using the Demirjian method. Accurate dental age estimation is crucial in forensic and clinical dentistry. Traditional methods for this purpose are typically time-consuming and require expertise, which increases the likelihood of human error. This study explored the potential of AI, particularly Vision Transformers (ViTs), to overcome these limitations. **Methods:** A number of 422 panoramic radiographs were analyzed, yielding 2,836 individual tooth images. The developmental stages of left mandibular teeth were determined according to the Demirjian method. Initially, 15% of the data was randomly separated for the test set. Subsequently, five-fold cross-validation was employed to partition the remaining data into training and validation sets. Three Convolutional Neural Network (CNN) models (ConvNeXt-Tiny, EfficientNet-V2-S, RegNet-Y-16GF) and three ViT models (ViT-B-16, Swin-V2-T, MaxVit-T) were trained using transfer learning. Model performance was evaluated using accuracy, precision, recall, and F1-score. The best-performing model, based on F1-score, was deployed in a web-based application. Mean Absolute Error (MAE) was used to assess the accuracy of AI-based age estimation compared to chronological age. **Results:** The Swin-V2-T model achieved the highest performance across all metrics (F1-score of 87%, Accuracy of 87.09%, Precision of 87.17%, and Recall of 87.09%). Analysis of AI-based age estimation accuracy revealed an MAE of 0.953 years. **Conclusion:** This study highlighted the applicability of AI, particularly ViT-based models, in automated dental age estimation using the Demirjian method. The developed AI model has the potential to streamline dental age assessments in both clinical and forensic settings, minimizing human error and enhancing efficiency.

Keywords: Dental Age Estimation; Artificial Intelligence; Vision Transformers; Demirjian Method

Introduction

Dental and skeletal growth are commonly being used as age indicators in clinical and forensic fields.[1, 2] Age estimation based on dental development is known as "dental age".[3] Compared to bones, the mineralization of teeth is less influenced by genetic diversity and environmental factors, making dental age a reliable metric for age assessment.[4, 5] In clinical dentistry, dental age estimation is valuable for planning orthodontic treatments and monitoring growth and development in pediatric patients. In forensic dentistry, it is instrumental for age estimation when chronological age is unknown or disputed.[4]

Dental age estimation methods can be broadly classified into three categories: morphohistological, biochemical, and radiographic methods.[6] Radiographic methods are the most commonly used due to their non-invasive nature and greater speed.[4] Radiographic approaches for estimating dental age include atlas methods, such as the Schour and Masseler method, and scoring methods, like the Demirjian method.[7] While atlas methods require direct reference to standardized images, scoring methods are preferred for their simplicity and higher accuracy in assessing dental development stages.[2]

The Demirjian method is the most widely used approach for age determination in children[8], developed by Demirjian, Goldstein, and Tanner through studies on French-Canadian children. Demirjian's dental developmental stages represent a simplified and refined version of the stages originally published by Moorrees, Fanning, and Hunt in 1963.[5]

In the Demirjian method, radiographs of the seven left mandibular teeth are analyzed. This method involves a three-step process: first, each tooth is assigned a stage from A (crown initiation and initial calcification) to H (apex closure and root completion) based on specific written criteria, schematic diagrams, and radiographic illustrations. Next, these stages are converted to numerical scores using gender-specific tables, and the scores are summed to obtain a Dental Maturity Score. Finally, this score is converted into dental age using additional charts or tables specific to each gender.[9]

Demirjian noted that, while the staging and scoring systems for dental development have broad applicability, the conversion to dental age may vary depending on the target population.[9]

Traditional methods, such as the Demirjian method, though widely accepted and used, face notable limitations. A significant drawback is the time and effort required for scoring-based methods.[10] For instance, a study by Kapoor et al. in 2018 reported an average of ten minutes needed to calculate an individual's chronological age using the Demirjian-Chaillet method.[11] Additionally, the subjectivity involved in manual assessments introduces varying degrees of intra- and inter-observer reliability issues.[10]

Artificial intelligence (AI) technologies have been extensively applied in various areas of dentistry, including caries detection, apical lesion identification, assessment of alveolar bone loss, osteoporosis detection, and the diagnosis of malignant lesions.[12] Previous studies have explored the efficacy of AI in determining age and gender based on dental radiographic images, demonstrating that AI—especially deep learning techniques—can address the limitations associated with traditional dental age estimation methods.[13] Recent work has continued to explore various deep learning approaches, including advanced CNNs, showing promising results in automating radiographic analysis for age assessment.[12, 14, 15]

Traditional Convolutional Neural Network (CNN) is a deep learning model widely employed in image processing and computer vision. It has long been the dominant architecture for computer vision tasks.[16] CNNs use convolutional layers to automatically extract hierarchical features from images, and are particularly effective in capturing local dependencies by applying small, localized filters across the input image, enabling feature maps to capture details like edges, textures, and shapes.[17] However, CNNs are inherently limited in capturing long-range dependencies due to the localized nature of convolutional filters and their fixed receptive fields, which typically require deep networks or complex architectures to approximate global context.[16, 17]

Vision Transformers (ViTs) [18], a newer class of architectures based on the Transformer model [19], was originally designed for natural language processing in 2020. This innovative deep learning model offers an alternative approach to visual processing by capturing both local and global dependencies through self-attention mechanisms. Unlike CNNs, ViTs divide an image into a sequence of smaller patches, treating each patch as a token similar to words in a natural language sequence, and apply multi-head self-attention mechanism to compute relationships between patches, granting it the capability to identify complex patterns.[18] This attention-based mechanism allows ViTs to model dependencies across the entire image from the start, enabling them to capture global context more effectively than CNNs, even at shallow depths.[16, 17]

Given the importance of accurate dental age estimation in clinical and forensic dentistry, alongside the limitations of traditional methods, this study aimed to develop an AI model for determining dental age in panoramic images based on the Demirjian method. While most prior research on AI-driven dental age estimation has primarily focused on CNN architectures, this innovative study examined the performance of more recent ViT models and compared their efficacy to that of CNN-based models.

Methods

Study Design and Population

This study employed a retrospective approach using 422 panoramic radiographs from the dental archives of Shahid Beheshti University of Medical Sciences. The study population included individuals aged 3 to 17 who had received panoramic radiographs for routine dental care between August 2021 and June 2023. Ethical approval for the research was obtained from the Ethics Committee at Shahid Beheshti University of Medical Sciences (approval code IR.SBMU.DRC.REC.1402.003).

Dataset Collection, Preprocessing, and Augmentation

Panoramic radiographs had been acquired using a CRANEX D imaging system (SOREDEX, Finland) with standard settings (70 kV, 10 mA, 17.6-second exposure time). All images were obtained as part of routine dental care, adhering to the ALARA principle (As Low As Reasonably Achievable). The images were retrieved from the faculty's Picture Archiving and Communication System (PACS) in PNG format with 32-bit depth. Data anonymization was performed by replacing personal information with unique research identifiers prior to inclusion in the study.

Each panoramic image was assessed for dental developmental stages using Demirjian's method by an evaluator who underwent thorough training in analyzing and interpreting dental development according to this method. To assess intra-rater reliability, a random subset comprising 10% of the images was re-evaluated after a two-week interval, with the agreement between initial and subsequent assessments calculated using the Linear Weighted Cohen's Kappa Coefficient.

The target tooth regions were carefully cropped and stored as separate files to prepare them as input for the AI model. Images with insufficient clarity in critical areas (particularly the incisors), improper positioning of the target teeth, dental anomalies in the teeth of interest, and prior dental interventions involving the left mandibular teeth were excluded. Preprocessing steps included histogram equalization, resizing, and pixel value normalization. Data augmentation techniques, such as random rotation, translation, scaling, and horizontal flipping, were applied to enhance model generalizability and performance across diverse dental images.

Data were categorized by tooth type (incisor, canine, premolar, and molar) and developmental stage (A to H) into distinct subgroups. Fifteen percent of the data were randomly set aside as a test set. The remaining data were divided into training and validation sets using 5-fold cross-validation, resulting in training and validation sets comprising 68% and 17% of the total data, respectively. This stratified partitioning ensured that the distribution of each subgroup was maintained across all sets.

Model Architecture

In this study, three models were utilized based on the traditional CNN architecture and three models based on the more recent ViT architecture, to compare their performance. Transfer learning was employed for all models. Details of the models are presented in Table 1.

Table 1- Summary of the deep learning models used for dental stage classification, including architecture type, number of parameters, and source of initial weights.

Architecture	Model	Initial Weights	Number of Parameters (Million)
CNN	ConvNeXt_Tiny (20)	IMAGENET1K_V1	28.6
	EfficientNet_V2_S (21)	IMAGENET1K_V1	21.5
	RegNet_Y_16GF (22)	IMAGENET1K_SWAG_E2E_V1	83.6
ViT	ViT_B_16 (18)	IMAGENET1K_SWAG_E2E_V1	86.6
	Swin_V2_T (23)	IMAGENET1K_V1	28.4
	MaxVit_T (24)	IMAGENET1K_V1	30.9

Model Training and Evaluation

Training employed a cross-entropy loss function with class weighting to address class imbalance and used the ADAM optimizer with a learning rate scheduler. Early stopping was incorporated to prevent overfitting, and models underwent a stratified 5-fold cross-validation to ensure generalizability. To thoroughly evaluate models' performance, the accuracy and weighted precision, recall, and F1-score were calculated. While accuracy provides an overall assessment and allows comparison with past studies, weighted metrics offer a more balanced evaluation by accounting for class imbalances in the dataset. Changes in these metrics were tracked throughout the training process. The model with the highest F1-Score was chosen for deployment. Additionally, the performance of this model was assessed and reported for the entire dataset as well as stratified by tooth type.

Model Deployment

The finalized AI model was deployed as a web-based application using the Streamlit framework, enabling dental age estimation from panoramic images. Streamlit was selected for its simplicity, rapid development cycle, and ability to create interactive applications with minimal overhead. This platform provided a user-friendly interface for uploading images, viewing developmental stage classifications, and computing dental maturity scores and dental age (Figure 1).

Age Estimation Performance

To assess the clinical applicability of the AI model, a separate set of panoramic radiographs, distinct from the previous dataset and spanning the period from June to December 2023, was collected. The exclusion criteria included inadequate image clarity in crucial regions (particularly the incisor area), improper positioning of target teeth that impeded developmental stage assessment, the absence or anomalies of the target teeth, previous dental interventions in the left mandibular region that interfered with evaluation, and cases with developmental disorders affecting tooth growth and development.

The objective of this phase was to compare the dental age estimated by the AI model with the chronological age. Dental age for each OPG (orthopantomogram) was determined using the developed application. Chronological age was calculated by subtracting the date of birth from the date of radiograph acquisition. The Mean Absolute Error (MAE) was used to compare the result of AI-assisted dental age estimation with the chronological age and results were reported both overall and by gender.

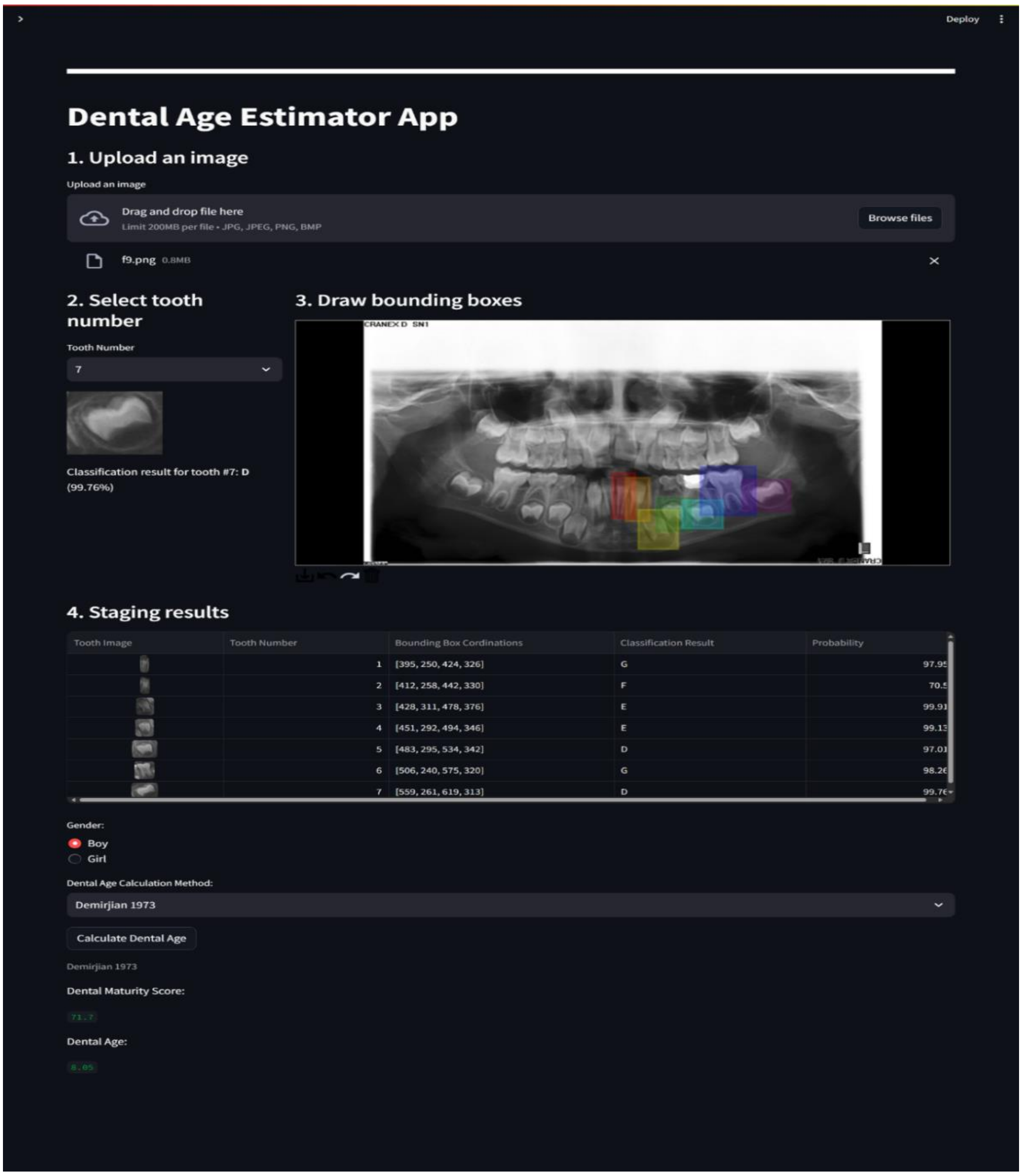

Figure 1: Web-based Dental Age Estimator App for classifying dental developmental stages and calculating dental age from panoramic radiographs.

Results

The final dataset consisted of 2,836 individual tooth images, extracted from 422 panoramic radiographs. These radiographs included samples from 201 male and 221 female patients, aged 3 to 17 years. Each tooth image was annotated according to its developmental stage (spanning stages B to H) and tooth type (incisor, canine, premolar, or molar). Table 2 provides a detailed breakdown of the dataset distribution.

Table 2- Distribution of dental image samples across tooth types and developmental stages (A–H)

Class	A	B	C	D	E	F	G	H	**Total**
Incisor	-	-	0	7	34	53	101	597	**793**
Canine	-	-	7	14	48	78	82	182	**411**
Premolar	0	10	25	60	117	133	129	336	**810**
Molar	0	11	27	64	62	76	205	378	**824**
Total	**0**	**21**	**60**	**145**	**261**	**340**	**517**	**1493**	**2836**

Intra-rater reliability was calculated using the Linear Weighted Cohen's Kappa coefficient, yielding a value of 0.93 for the complete set of teeth (incisors: 0.90, canines: 0.87, premolars: 0.94, and molars: 0.94), indicating excellent agreement.

Figures 2 through 5 illustrate the performance of the six models on this dataset based on each evaluation metric. As shown in these figures, the Swin Transformer V2 model consistently outperformed other models across all metrics. Notably, it achieved the highest accuracy (0.87 in Fold 2) and average accuracy (0.818), the highest precision (0.87 in Fold 2) and mean precision (0.850), the highest recall (0.87 in Fold 2) and mean recall (0.818), and the highest F1-score (0.87 in Fold 2) and mean F1-score (0.824). These results established Swin Transformer V2 as the model of choice for deployment.

Table 3 presents a comparison of this model's performance across different tooth types. Figure 6 depicts the model's performance in classifying various dental development stages using a confusion matrix. The results of the subgroup analysis indicated that the model achieved its highest performance across all metrics in the premolar subgroup. This was followed by the incisor and canine subgroups, which exhibited performance levels similar to the overall model performance. Lastly, the molar subgroup demonstrated comparatively lower performance than the other subgroups. The results indicated variability in classification performance across different developmental stages, with the highest accuracy observed for stage H (0.92) and the lowest for stage C (0.33). Notably, all misclassifications occurred within adjacent stages.

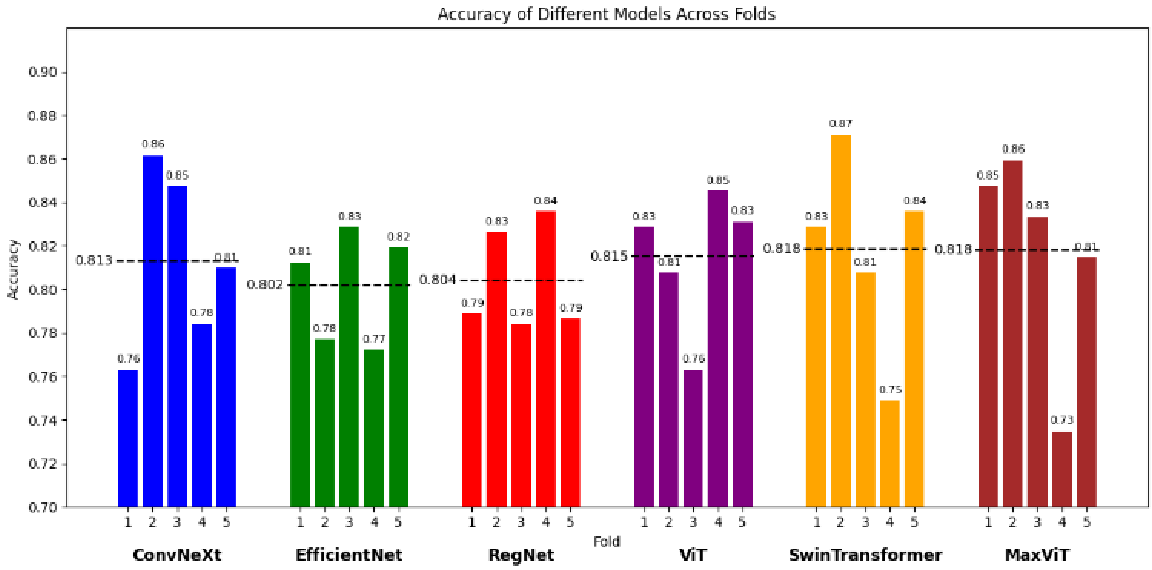

Figure 2: Accuracy of six deep learning models across five cross-validation folds.

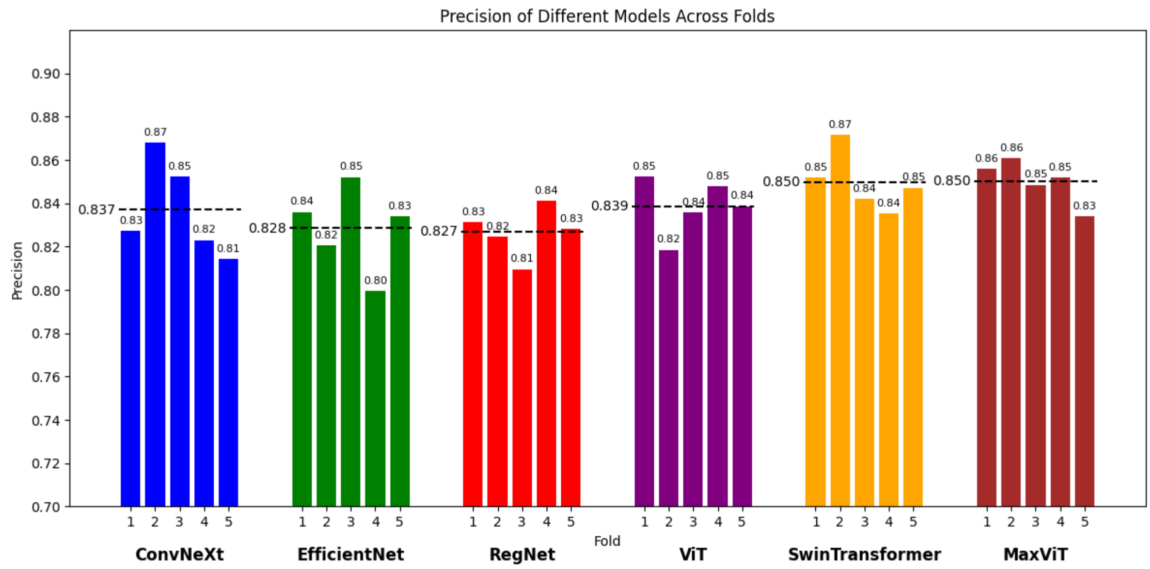

Figure 3: Precision of six deep learning models across five cross-validation folds.

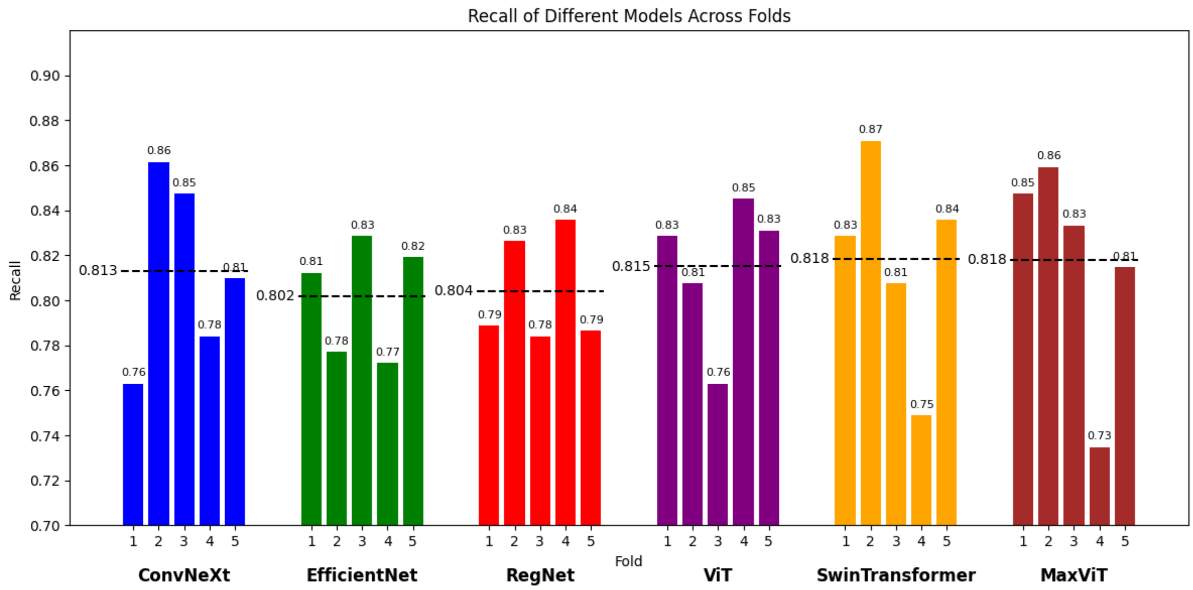

Figure 4: Recall of six deep learning models across five cross-validation folds.

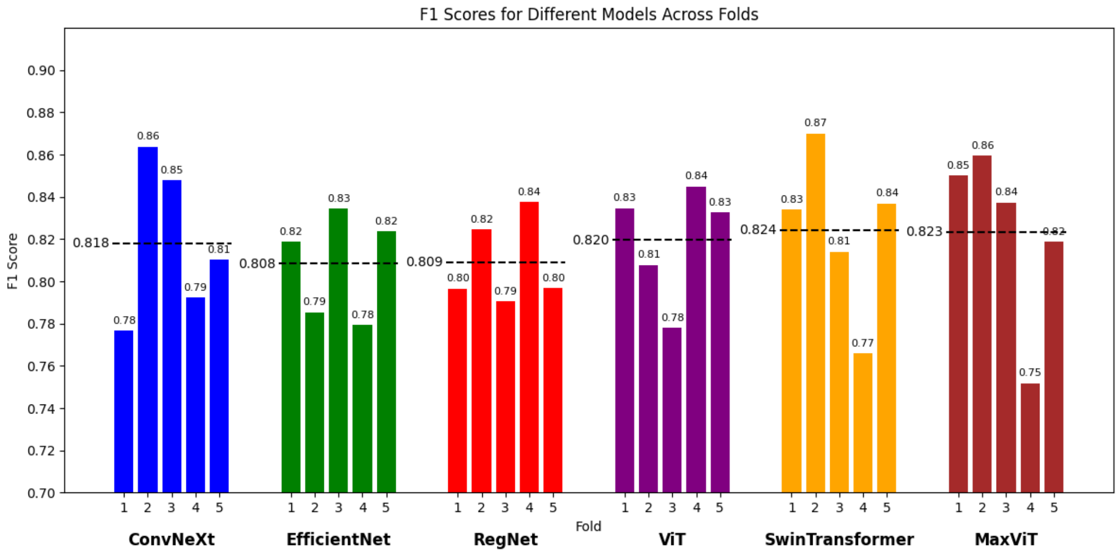

Figure 5: F1-score of six deep learning models across five cross-validation folds.

Table 3- Performance metrics of the model across different tooth types.

Subgroup	Loss	Accuracy	Precision	Recall	F1-Score
Incisor	0.4288	0.8908	0.8874	0.8908	0.8881
Canine	0.3227	0.8689	0.8678	0.8689	0.8669
Premolar	0.7425	0.9098	0.9097	0.9098	0.9070
Molar	0.9290	0.8145	0.8227	0.8145	0.8126
Overall	0.6762	0.8709	0.8717	0.8709	0.8700

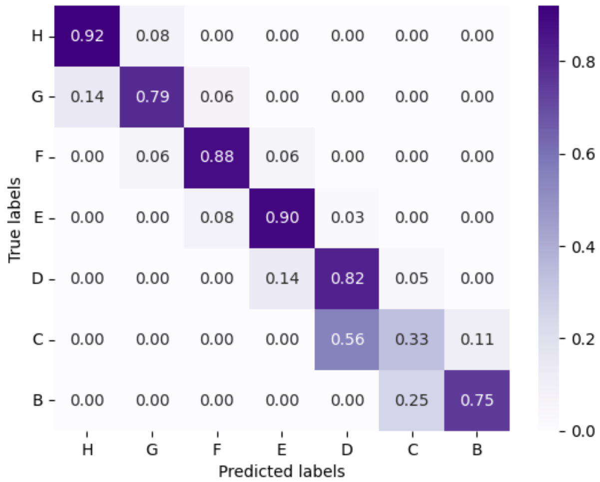

Figure 6: Confusion matrix showing the model's performance in classifying dental development stages.

Discussion

This study aimed to develop an AI model for dental age estimation in panoramic radiographs based on Demirjian method. The primary objective was to create a model capable of accurately classifying dental development stages, thereby streamlining and expediting the dental age determination process while minimizing human error and improving both intra-observer and inter-observer reliability.

The findings indicated that models based on the ViT architecture outperformed CNN-based models in classifying dental development stages. ViT-based models leverage their self-attention mechanism to evaluate relationships between all parts of an image, regardless of their physical distance. Comparative analyses of information processing in CNN and ViT architectures have shown that while CNNs initially focus on local details before progressing to broader structures, ViTs have access to the overall context of the image from the outset. These findings suggest that vision transformers' ability to capture complex relationships within images through self-attention can be highly beneficial for accurately classifying various stages of dental development.[16, 17]

Specifically, the Swin-V2-T model's success over the other tested ViT architectures (ViT-B-16, MaxVit-T) in this study may stem from its use of shifted windows within a hierarchical structure. This approach allows for efficient modeling of relationships at different scales while maintaining computational efficiency, which appears particularly advantageous for capturing the subtle, multi-scale features relevant to dental development stages in panoramic radiographs compared to the standard global attention in ViT-B-16 or the multi-axis attention in MaxVit-T.[23, 25]

The present findings align with recent trends in medical image analysis, where ViT-based models have demonstrated promising results.[17] For instance, studies by Tyagi et al. [26], Wu et al. [27], and Gheflati et al. [28] have highlighted the efficacy of ViT models across various medical imaging tasks. These findings underscore the growing success of ViT models in analyzing medical imaging data. However, to the best of our knowledge, this research represented one of the first studies to specifically apply and compare these advanced AI architectures for dental age estimation using Demirjian method.

Table 4 compares the results of our study with similar studies aimed at automating the classification of dental developmental stages for teeth 31 to 37 using Demirjian's 8-stage method.

Table 4: Comparison of our model's performance with previous studies on automated classification of dental developmental stages (teeth 31–37) using Demirjian's 8-stage method.

Study	Dataset Count	Model	Accuracy	F1-Score
Aliyev et al. (2022) (14)	475 OPGs	Custom CNN	0.704	0.68
Ong et al. (2024) (12)	5133 OPGs	EfficientNet		0.6923, 0.8067, 0.8497, 0.9081
Kurt et al. (2024) (15)	1500 OPGs	YOLOv5		0.84
Our Study	422 OPGs	Swin_V2_T	0.8709	0.8700

The present study indicated that the model demonstrated its best performance in the premolar subgroup, followed by the incisor, canine, and molar subgroups, respectively. Regarding the classification of dental developmental stages, the model achieved the highest accuracy in stage H, while the lowest accuracy was observed in stage C. These results suggest that the model excels in identifying the later stages of dental development, such as stage H, but faces greater challenges in earlier stages like stage C.

The model's relatively lower performance in molar teeth may be attributed to the fact that single-rooted teeth exhibit more similar developmental stages. Due to the higher number of these teeth in the training data, the model tends to learn their characteristics more accurately, leading to better results for these teeth.

The variation in the model's performance in classifying different developmental stages can be attributed to the limited availability of samples from the earlier stages in the dataset. When fewer samples are available for these initial stages, the model has less opportunity to learn them effectively, which may result in reduced accuracy in detecting these stages. Additionally, these differences may stem from the inherent complexity of certain stages or the high similarity between consecutive stages, which can make differentiation more challenging. Furthermore, stages C and D often overlap with primary teeth or appear rotated in radiographs, complicating the model's ability to accurately learn and classify these stages.[12]

The successful implementation of AI in the automatic assignment of Demirjian's developmental stage has significant implications for various fields of clinical and forensic dentistry. In clinical dentistry, this model is valuable for planning orthodontic treatments and monitoring the growth and development of pediatric patients. In forensic dentistry, it proves useful when an individual's chronological age is uncertain or disputed. By eliminating the subjectivity inherent in manual assessments, this model reduces variability both within and between observers while also improving the accuracy and efficiency of age estimation. Furthermore, in large-scale studies related to dental development assessment across diverse populations, the speed and accuracy of this model provide a considerable advantage.

While the current study demonstrated promising results, several limitations should be acknowledged. A key constraint was the insufficient data available for some stages of each tooth group, which potentially could impact the performance evaluation of the models. The imbalanced dataset between developmental stages, particularly with fewer samples for early stages, may have affected the accuracy of the classification model. These limitations highlight the areas that require further attention to improve the model's performance.

Future research should focus on addressing the limitations mentioned in this study by expanding the dataset to include a more balanced representation of tooth developmental stages, particularly for the early stages where fewer samples were available. Additionally, further studies should explore the potential of other advanced deep learning algorithms and techniques to determine whether these can offer improvements in accuracy of developmental stage classification. Future research could also investigate the generalizability of the model by incorporating multi-center data obtained from diverse imaging equipment. This would enhance the robustness and applicability of the AI tool in diverse clinical and forensic settings. These efforts could lead to significant advancements in the field and provide valuable insights for more accurate dental age assessments. Future works also should include developing tailored user interfaces to facilitate seamless integration into existing workflows, as well as conducting prospective studies to validate the AI model’s performance in real-world clinical and forensic settings.

Conclusion

This study represented a significant step forward in the application of AI for dental age estimation using the Demirjian method. The findings demonstrated that AI, particularly ViT-based models like Swin_V2_T, can effectively perform the assignment of dental developmental stages. This research contributes to the growing body of evidence supporting the use of AI in dentistry. As AI technology continues to evolve, we can expect further advancements in dental age estimation and other applications, paving the way for more efficient, accurate, and objective dental assessments.

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Ethical Approval Code: This study was approved by the Ethics Committee of Shahid Beheshti University of Medical Sciences (approval code IR.SBMU.DRC.REC.1402.003).

Informed Consent Statement: This study employed a retrospective approach using panoramic radiographs from the dental archives of Shahid Beheshti University of Medical Sciences. Data anonymization was performed by replacing personal information with unique research identifiers prior to inclusion in the study, hence no informed consent needed.

Data Availability Statement: The datasets generated during and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Using AI: This manuscript was written entirely by the authors without the assistance of any AI tools or large language models.

Conflict of Interest: The authors declare no conflicts of interest related to this work.

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