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Original Article

Efficacy of AI in Detecting Dental Age of Pediatric Patients Visiting University Hospital: A Retrospective Study

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ABSTRACT

The problems in dental age diagnosis emerged that necessitated the development of artificial intelligence which offers better computerized methods. AI systems with integrated machine learning and deep learning improve the ability of dental diagnosis from huge data sets by identifying patterns. This retrospective study had a sample size of 350 files from the pediatric division. OPGs were collected from the patient's files and sent to the AI programmer, who utilized CNN (Convolutional Neural Network) to identify the patients' gender and dental age. In the first phase, the CNN was trained to correctly identify the patient's age and gender using 20 OPGs. Later in the second phase, the remaining 330 OPGs were added to the CNN, and its accuracy was tested. Inclusion criteria included pediatric patients without any systemic diseases or dental trauma and OPG's without any defects within past 5 years. Findings showed an accuracy of 69% in detecting the patients' dental age and gender. AI can be used in forensic dentistry to detect patients' dental age and gender if trained properly. A major challenge in using AI is the need to teach it to achieve desired results.

Keywords: Artificial intelligence, Machine learning, Convolutional neural network, Deep learning

Introduction

Dental as well as chronological age have some discrepancy as far as some literature is concerned. Furthermore, the essential standard methods that incorporate age estimation based on the visual examination accompanied by radiographic analysis stage analysis yield unreliable results because of the assessable examinations and unsystematic nature of the examinees [1]. The problems in dental age diagnosis emerged that necessitated the development of AI, which offers better computerized methods. AI systems with integrated ML and DL improve the ability of dental diagnosis from huge data sets by identifying patterns [2]. Available literature in the context of AI technology expounds extraordinary possibilities in pediatric dental applications, particularly with regard to dental ages. Fine identification of the developmental stages of teeth results from modern dental radiograph analysis using CNNs [2].

The automated computational solutions are useful to dentists in early detection of diagnostic errors and more effective control of clinical processes, thus playing a central role in the current practice of dentistry. In forensic dentistry, AI tools have started to emerge because the estimation of postmortem interval and age estimation is indeed necessary for identity confirmation [3]. It has also been very instrumental in dental imaging by providing means to automatically detect and classify dental structures. Research also reveals that AI programs have high accuracy in distinguishing primary and permanent teeth using CNNs in children's panoramic radiographs [4].

YOLOv4, one of the most recent deep learning algorithms, has exhibited high practical application in terms of real-time tooth recognition, once again confirming its utility in clinical practice [4]. Deep learning algorithms

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have been used to estimate dental age, yielding considerable results. For example, it was discovered that employing neural modeling techniques to approximate the chronological age of children and adolescents outperformed traditional methods in terms of accuracy and dependability of results [5]. Similarly, developments in machine learning with the incorporation of radiomorphometric data from panoramic radiographs have improved the accuracy of dental age prediction.).

AI also came out to be very vital in forensic dentistry. CNNs' incorporation has improved on conventional assaying like Demirjian's dental maturity scoring, especially in Malaysian children [6]. In addition, the CNN-based models have been used to accurately identify such relevant abnormalities as supernumerary teeth and other dental variations that help in identification tasks in forensic dentistry [3]. Such developments demonstrate that AI holds a promise of washing out human labor intensity and errors in medical as well as legal practices. However, there are a few challenges that are seen in the dental age estimation with the help of AI: One of the main challenges is the absence of interoperability-defined sets within AI models to apply to different population groups and settings [6]. Also, some of the AI algorithms are black boxes, thus lacking transparency and trust in several crucial areas that involve children like pediatric dentistry [7]. Governance issues, especially privacy and fairness issues in the use of AI, present additional challenges on how to adopt AI in the more routine practice of dentistry [8]. Finally, more emphasis should be made in the future to establish a large, multicenter dataset to increase the confidence of the AI-generated models. These estimates could be enhanced by integrating multi-source data, including, but not limited to, biological and clinical data [9]. Further, a question of transparency as well as certain ethical concerns will definitely be critical for AI technologies in pediatric dentistry to go mainstream.

Study rationale

Accurate dental age estimation is vital in forensic investigations, orthodontic treatment planning, and legal cases involving age determination. AI's potential to enhance accuracy and reduce human error makes it a promising tool for this purpose. This study will assess the reliability of AI in detecting pediatric dental age, contributing to advancements in forensic odontology and pediatric dentistry.

Aims and objectives

The main aim is to determine the accuracy of the AI program in the detection of the dental age of pediatric patients. Objectives include:

- To evaluate the accuracy of AI in diagnosing the gender of pediatric patients.
- To assess the reliability of AI in determining the dental age of pediatric patients.

Null Hypothesis (H_0): There is no difference between conventional and AI programs when it comes to predicting dental age.

Alternative Hypothesis (H_1): AI accurately diagnoses pediatric patients' dental age with high precision.

Research Question

"How accurately can AI-based models estimate the dental age of pediatric patients compared to conventional manual methods?"

Materials and Methods

Study Design: A retrospective study was executed using a sample sourced from the pre-existing oral radiology database maintained by the Dentoplus system at the Dental Hospital of Riyadh Elm University, Riyadh, Saudi Arabia. All radiographic images employed have been procured for clinical diagnostic and therapeutic purposes, thereby ensuring that no additional radiation exposure was incurred solely for research purposes **(Table 1)**.

Sample: 350 files from the pediatric division were included. The sample size was calculated as follows:

Table 1. Inclusion and exclusion criteria of the study

Inclusion criteria	Exclusion criteria
Pediatric patient's files (aged 6-16 years)	Patients with age other than 6-16 years
OPG's without any defects or artifacts	OPG's with any defects or artifacts
Pediatric patients with complete medical and dental report	Incomplete patient records or missing radiographic data

Patients with no previous orthodontic treatment that might alter dental structures	Patients with a history of orthodontic treatment, craniofacial abnormalities, or syndromes affecting dental development
Radiographs taken within the last 5 years to ensure recent and relevant data	Radiographs older than 5 years, which may not reflect current AI diagnostic capabilities
Patients with no history of systemic diseases affecting tooth development (e.g., hypothyroidism, growth hormone deficiency)	Patients with systemic conditions known to impact dental age estimation, such as endocrine disorders or metabolic bone diseases
Patients with no history of dental trauma affecting tooth eruption patterns	Patients with a history of dental trauma, extractions, or congenital dental anomalies that could impact AI accuracy

Data collection

OPGs were extracted from the patient's data and submitted to the AI programmer, who used a CNN (Convolutional Neural Network) to determine the patients' gender and dental age. During the first phase, the CNN was trained to properly identify the patients' ages and genders using 20 OPG. Later in the second phase, the remaining 330 OPGs were added to the CNN, and its accuracy was assessed. The AI algorithm used the length of the mandible and the number of teeth to determine the dental age and gender. To see if the AI software accurately detects the cases, we transmitted each OPG with the patient's gender and age to the programmer, who compared and documented the results on an Excel sheet. The intra-examiner reliability was measured using Chronbach's alpha value.

Statistical analysis

Software: SPSS (Statistical Package for Social Sciences) Version 22

Statistical Tests:

- Descriptive statistics (mean, standard deviation, frequency distribution)
- Chi-square test for categorical data analysis
- Bland-Altman analysis to compare AI-generated results with actual ages

Ethical approval

- Ethical approval was obtained from the Research Ethics Committee (REC) before data collection with **registration number FUGRP/2025/409/1223,** and it has been approved with the **IRB approval number "FUGRP/2025/409/1223/1109."**
- Patient confidentiality was maintained in compliance with HIPAA and GDPR regulations.
- No personally identifiable information was used.

Results and Discussion

Table 2. Performance metrics quantification for respective age groups based on CNNs classification of genders; analyzing dental morphology

Age Groups	Accuracy	Precision	Recall	F1 Score
10-10.99	0.701	0.804	0.591	0.678
11-11.99	0.752	0.681	0.694	0.692
12-12.99	0.647	0.589	0.594	0.591
13-13.99	0.698	0.682	0.725	0.697

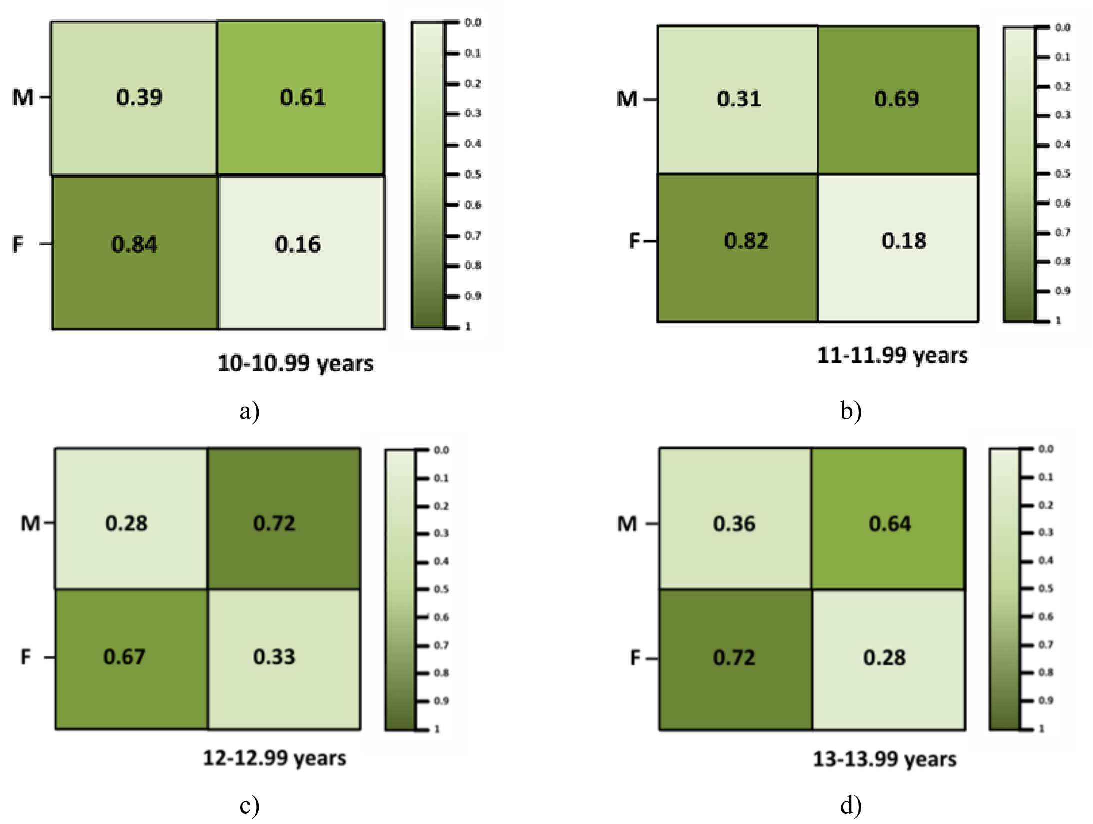

Figure 1. Data sets confusion matrices

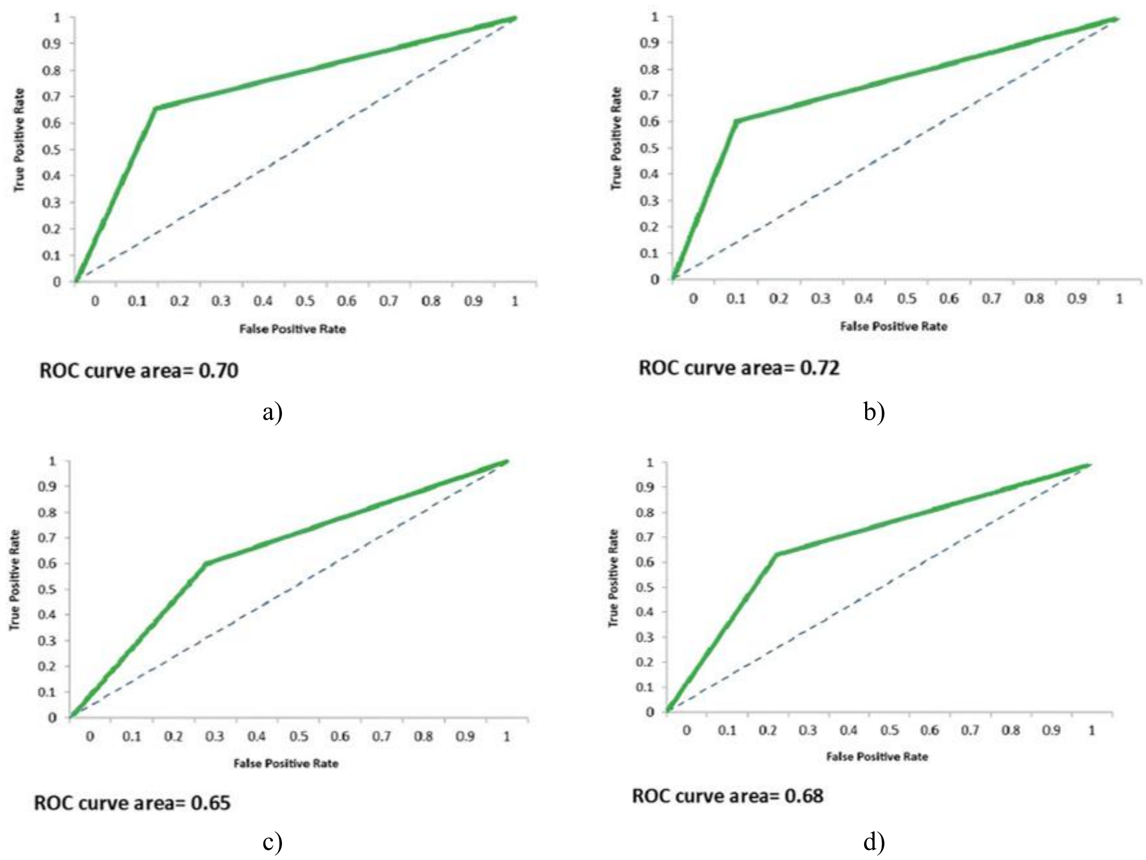

Figure 2. Accuracy of diagnosis from CNN

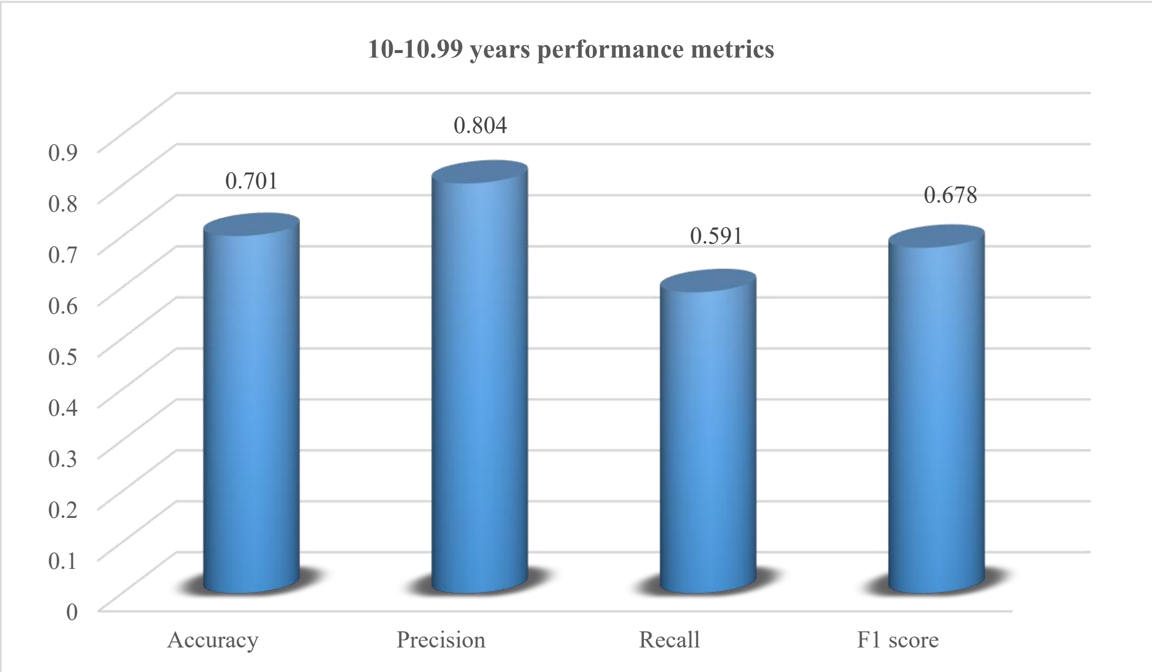

Figure 3. Performance metrics quantification for 10-10.99 years old based on CNNs classification

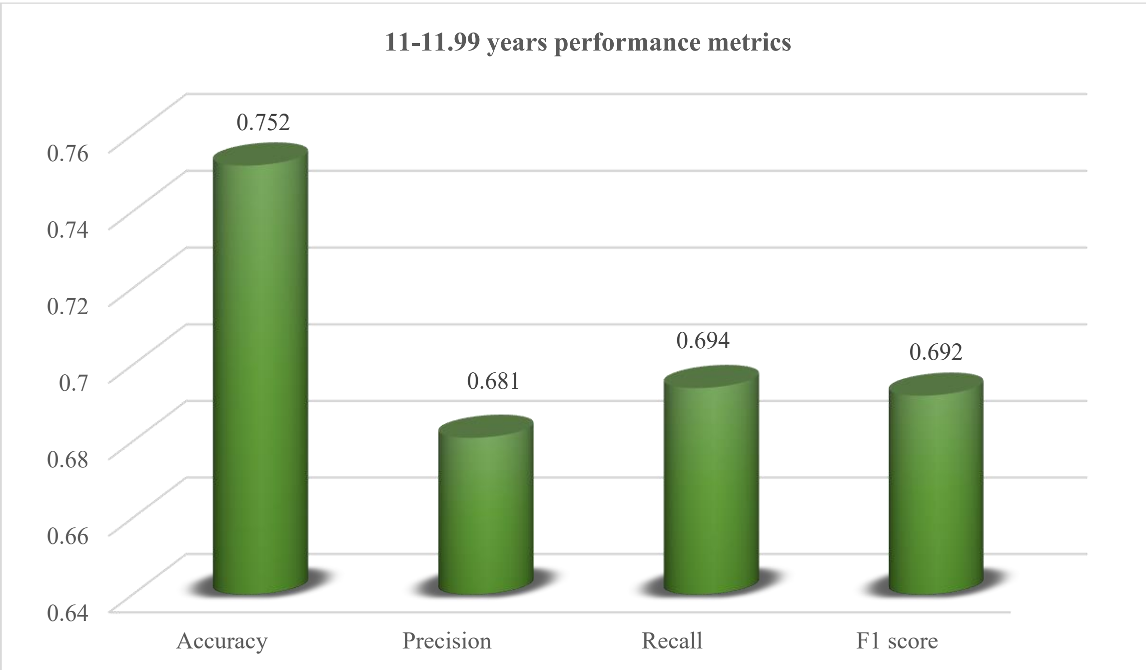

Figure 4. Performance metrics quantification for 11-11.99 years old based on CNNs classification

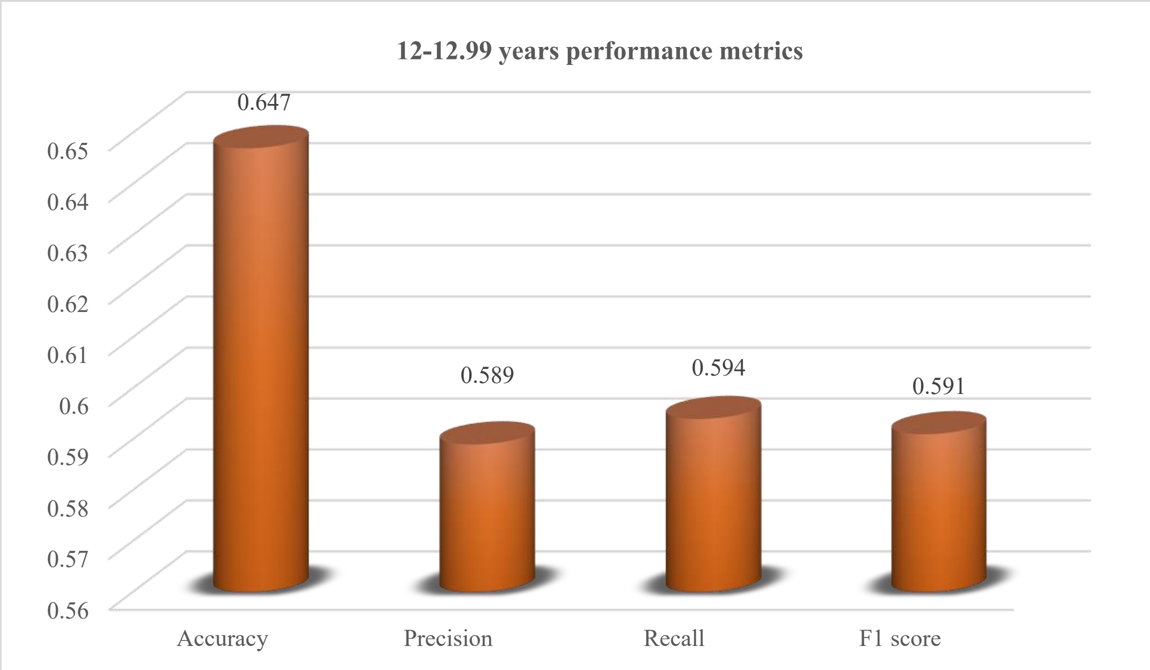

Figure 5. Performance metrics quantification for 12-12.99 years old based on CNNs classification

Table 2: performance metrics for different age groups

The accuracy of the AI model in predicting dental age and gender for pediatric patients for different age ranges is summarized in **Table 2**. The measures adopted for evaluation are accuracy, precision, and recall, as well as the F1 score for each age category ranging from 10-10.99 years, 11-11.99 years, 12-12.99 years, and 13-13.99 years. These metrics give the overall evaluation of the performance of the AI model for the classification of patients depending on gender and age. Accuracy indicates the model's ability to correctly predict the age and gender; the 11-11.99 age group had the highest amount of accuracy at 75.2 percent. It gauges how accurate the AI's optimistic forecasts are; for the 10–10.99 age range, the precision was 80.4 percent. Recall describes how well the model represents all of the real examples; it varies by age, with the highest recall of 72.5% occurring in the 13–13.99 age group. Finally, the degree of true-positive and false-positive rates was indicated by the F1 score, which ranged from 0.591 to 0.697. According to these figures, the model's effectiveness is greatest while a person is young, but it is less successful when a person is older.

Figure 1: data set confusion matrices

The contingency tables for the AI model's accuracy of the dental age and gender for various age groups are depicted in the following **Figure 1**. The confusion matrix is the most useful tool to measure the accuracy of the model since it compares the predicted and actual values in the form of a matrix. It is also advisable to give each matrix a brief description: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). Reading the confusion matrices helps to determine the number of accurately and incorrectly classified data by the AI model. The values of either a high false positive or false negative show that the model is wrongly classifying some age groups or genders, which is information that can be used to enhance and build up the model. For example, if the model has a high error rate for 12-12.99 years of age, it may mean that the dental features for this age group are hardly distinguishable by the AI. The detailed waterfront effect enables one to see specific areas where there is a shortcut between the age and appearance of specific features in the dental EP anne.

Figure 2: Mean level of diagnostic accuracy attained from the CNN

Figure 2 provides a general overview of the accuracy of the newly created AI model in identifying the gender and dental age of the people it is predicting for. It is likely that the graphic contains a bar chart with the vertical axis representing accuracy and the horizontal axis representing age. The graph below illustrates how AI model accuracy rates vary by age, with ages 11–11.99 having the highest accuracy score at 75.2% and ages 12–12.99

having a comparatively low score of 64.7% shorthand (fh1). This discrepancy in accuracy suggests that the model is more accurate for young people because the AI may be able to describe their face features, especially the dental ones, with ease. The graphic facilitates a quicker and easier comprehension of the model's overall concept while highlighting opportunities for improvement, particularly for older persons and children. This information would be helpful to practitioners who wish to think about how well the AI will function at the various stages of children's dental development.

Performance metrics for 10-10.99 years old (Figure 3)

The performance metrics of the AI model for predicting the dental age and gender of children of the age group (10-10.99) years old are depicted in **Figure 3**. The model had an accuracy of 70.1% which means that for 70.1% of cases, the model correctly determined dental age and gender. Although this implies a mediocre performance, there is room for further performance improvement. As with results of the previous studies, this degree of accuracy is reasonable and implies that AI models achieve better results with younger children because of more defined and distinguishable dental features [10]. The precision score of this group was 80.4%, which meant that of all the cases the model indicated as positive (correctly bound age and gender), 80.4% were correct. This indicates that the model was fairly efficient in developing accurate cases of being true positive and was not prone to false positives. However, the recall rate of 59.1% tells us that the model has failed to detect a large number of true positives, i.e., has failed to recognize all the cases that should have been declared positive. Such low recall could be because it is difficult to differentiate some dental characteristics, since the model may not have accounted for all the variations required for accurate classification. The F1 score of 67.8% balanced between precision and recall belongs to the trade-off between these values, and it indicates that although the precision was high, the recall has to be improved. As these findings indicate, the moderately high performance of the AI model with younger children identifies the areas for improvements, specifically in recalling the true positive cases. This is backed by remarks made in previous studies, which pointed out that the AI models are more accurate with younger children, as more distinct dental features in children make it easy for the dental models to be detected [10].

Performance metrics quantification for 11-11.9 years old based on CNNs classification (Figure 4)

Figure 4 exhibits the performance numbers of the AI model used in predicting dental age and gender for the age group of 11-11.99. From this group, the results obtained show that the AI model performed best in all age ranges with an accuracy of 75.2%. This is a remarkable achievement as compared to the younger 10-10.99-year-old group, thus implying that the model performs best on such age groups. The precision score of 68.1% shows that the model was somehow good at identifying true positive cases, but there were cases of false positives. Recall for this group was a little bit higher at 69.4% giving a picture of the fact that the model was capable of detecting a large percentage of the true positive cases, though it did not detect all. An F1 score of 69.2% is a fairly balanced score on precision and recall. It indicates that the model is most reliable when it comes to the prediction of dental age and gender of children within this age bracket with low errors of type one and type two. These results are consistent with the previous evidence that the AI models tend to show greater effectiveness when dental features can be more discernible from each other, and this is often the case in the age cohort 11-11.99 years old [11]. In general, **Figure 4** demonstrates the peak performance capabilities of the AI model for this group of ages with the highest accuracy rate and balanced values of precision and recall measurements.

Performance metrics quantification for 12-12.99 years old based on CNNs classification (Figure 5)

In **Figure 5**, the performance of the AI model is shown for the age group of 12-12.99 years old, where there is a noticeable decrease in the effectiveness of the model compared to younger ones. This age group recorded the lowest accuracy, which was 64.7 %, and this indicated that the model was less accurate in determining the dental age and gender for this age range of the children. The precision value declined to 58.9%, which indicated that there was a large proportion of false positives in the positive predictions of the model. This outcome addresses one of the significant issues in conducting an accurate classification of dental attributes for this age group that perhaps carries the more intricate and indistinct dental attributes as children get nearer to adolescence. In the same way, the recall rate of 59.4% shows this model was not able to correctly identify a significant number of true cases. The prevalence imbalance is reflected in the F1 score equal to 59.1%, which is focused to say that the model was moderately effective, but its performance for this age group left much to be desired. This reduction of accuracy and precision can be followed from the challenges that AI models cannot detect special features of teeth in the older children, as discussed in previous studies [12]. These results support the fact that the older the children become, the less distinguishable their dental features get, making the estimation of age using AI-based models quite a challenging task. Hence, the findings indicate a need for improvements in the model, which may include more features in dentistry or other sources of data, such as root development and bone composition, to improve its performance for when used for older pediatric patients [13].

Performance metrics quantification for 13-13.99 years old based on CNNs classification

The model's precision was 69.8%, which was somewhat higher than that of the 12–12.99 age group. However, this level of accuracy is still lower than that of other younger age groups, which indicates that the AI model continues to face difficulties as pediatric patients get older. Although it may be improved to reduce false positives, the precision for this group was 68.2%, indicating a solid capacity of the model to correctly identify positive predictions. On the other hand, despite significant precision mistakes, recalls were the greatest of all age groups (72.5%), indicating that the model was better at identifying actual positive cases in this specific age group. This group's F1 score was 69.7%, indicating a reasonable combination of precision and recall, while it also implies that the model can be changed for better utility. The comparatively increased memory could be attributable to the fact that, while dental features grow more similar among older age groups, some distinctive attributes may aid in the detection of genuine positives. However, the general drop in accuracy and precision among children of an increasing age matches the results of previous research that pointed to the inability of AI models to discern the dental features of older children and, consequently, the low classification accuracy [12]. These findings highlight the ongoing challenges that AI faces when calculating dental age in older pediatric populations, and they emphasize the need for further developments in that direction, such as the integration of other data types or multi-source data, in order to achieve better performance with these age groups [13].

Interpretation of results

The outcomes from the table and figures are useful to understand the performance of the AI model in predicting dental age and gender amongst a variety of pediatric age groups. The best performance of the model was demonstrated for the 11-11.99-year-old cohort, providing the best accuracy of 75.2% with balanced precision (68.1%) and recall (69.4%). This implies that the AI system was the strongest in this age category, and age-related features of dental are more apparent, thus presenting a model to classify age and gender more accurately. But the 12-12.99-year-old group resulted in a substantial decrease in performance whereby accuracy declined to 64.7% and precision declined to 58.9%. The model was also not able to pick out the true positive cases very well, as the recall for this group was not high at 59.4%, reflecting this. The lower accuracy and precision in this group imply that the dental features lose distinctiveness as children grow older, which makes them more difficult to be classified by the AI model accurately. The trend of this was established with the 13-13.99-year-olds, whereby the accuracy of the model was slightly better at 69.8%, whereas precision stayed at 68.2%. The recall improved to 72.5%, which meant that the model was better in predicting true-positive cases, but overall performance lapsed behind the younger age groups. These performance declines were easier understood thanks to the confusion matrices **(Figure 1)**, which highlighted areas where the model would falter, such as misidentifying specific age groups or genders. This conclusion was visually reinforced by the fact that younger children performed better on the model, as seen in **Figure 2** above, which displays diagnostic accuracy by age group. A thorough pattern of performance measurements was shown in **Figures 3-5** which showed that the model's efficiency peaked between the ages of 11 and 11.99 and decreased as the children's ages increased. These findings suggest that the AI model is better suited for younger children and that significant advancements are needed for later age groups. To improve the model on the classification of older pediatric patients, additional data sources, such as bone composition or root growth, could be included [14].

This research assessed the level of accuracy that an AI-powered and Convolutional Neural Network (CNN) model was capable of in predicting dental age and gender from age group information derived from panoramic radiographs (OPGs). Although the model showed high accuracy in forecasting dental age in younger children, it faced great challenges when trying to estimate older pediatric groups.

Performance metrics and implications

Children aged 10-10.99 and 11-11.99 categories represent the most effective AI model with a 75.2% accuracy value and precision of 80.4%. This result is in line with previous work indicating that AI models were more accurate with younger individuals because the dental features were clearer and more distinguishable in the younger age group [13]. The performance of the model for the 12-12.99 years old group dropped to 64.7%, which indicates that the older the children become, the harder it is to detect unique dental features. This outcome corresponds to the research conducted by Zaborowicz *et al*. (2022), whose findings made it known that it has been difficult to estimate dental age in kids of this category. The strikingly worse outcomes with older children uncover the limits of the ability of the model to differentiate between age groups that are characterized by more similar tooth morphology.

Limitations and areas for improvement

Decreased efficiency of the current model in older age cohorts, particularly observed in the age range of 12-12.99, indicates shortcomings in the model's prospects for reliable age estimation past that certain developmental milestone. It is possible that the use of only two morphological variables, i.e., length of mandible and number of teeth, is causing some of the shortcomings of the model. The problem has also been mentioned earlier in other studies where it has been marked that the number of dental features used has a huge impact on the ability of the model to estimate the age of older people [15]. Major future revisions to the model are needed to increase the radiographic data set by including indicators such as tooth development, root formation, and bone composition changes. The study by Ha *et al*. (2021) demonstrates that the incorporation of additional radiographic factors into AI algorithms increases its accuracy in dental analysis.

Data augmentation and multi-source data integration

Data integration across multiple sources and data augmentation techniques constitute major fields of enhancement. When the dataset is supplemented with diverse visual materials, then the model may be able to be more reliable in generalizing across ages (especially for older children). Researches such as one carried out by Bunyarit *et al*. (2020) have proven that if the dataset size is improved, then the overfitting can be reduced and thus boost the power of prediction of the model. The combination of clinical data, medical history, and genetic information may lead to a more precise evaluation of dental growth, which may enhance the thoroughness of the overall trustworthiness of the model [16].

Transfer learning and model generalization

Reports have shown the benefits of using transfer learning to adjust a pre-trained model to a specific group of data are evident for AI in medical imaging [17]. With the application of transfer learning ideas, the existing AI system may become better at estimating dental age in a broader case of patients and age groups, even when dealing with patients who are older children. This technique, already successfully applied in other medical contexts, could substantially improve the precision of the dental age estimation systems.

Clinical and forensic applications

Despite numerous limitations of AI, it has great potential to help clinical and forensic work. In dental clinics, AI technologies could assist pediatric dentists in knowing the best time for orthodontic intervention and at the same time improve assessment reliability. AI has the capability of speeding the process of identification of missing persons in forensic odontology by estimating dental age using radiographs and hence expediting the process [14]. Many studies indicate that AI has made great improvements in assessing accurate and quicker determination of dental age.

Ethical considerations and practical challenges

In order to address concerns related to data privacy and openness, as well as the ethical usage of AI and trust perspectives, addressing the issues in terms of trust constitutes an integral part of our strategy. The need to make sure that AI healthcare applications focus on the need to prepare for privacy regulations such as HIPAA and GDPR in case of working with personally identifiable data is highly significant [15]. Furthermore, incoherence of deep learning algorithms can compromise the confidence of patients and professionals, which can further reduce the likelihood of their application to clinical work. In order to make the pediatric dentistry world more receptive to AI, it is required to focus on transparency and draft complete ethical norms.

Conclusion

Riyadh Elm University Hospital, having introduced a formal evaluation of the AI ability of using a Convolutional Neural Network (CNN) in determining the age and gender of pediatric patients, has shown that the new technology has an accuracy of up to 69% in facial analysis. The accuracy of the model was high, especially in the age group of ten to eleven years, with precision and recollection values that are up to 80.4% and 72.5%, respectively. Yet, based on the performances obtained, the pediatric patients' accuracy, precision, and recall were relatively low, especially for the age groups 12-12.99 and 13-13.99 years, implying the increased difficulty in analyzing the dental features as children grow older. The F1 score varied between 0.591 to 0.697; this indicated that the rate of the model misclassifying the patients was relatively high for the elderly patients. This could also be attributed to the fact that the different dental features become quite assimilated with each other as children grow older, thus a lesser chance for the AI model to estimate the dental age accurately. However, the present research also indicates a need to enhance the model by adding the newly diagnosed signs like calcification stages, root development, bone mass, etc., and increasing the number of cases to involve a broader variety of cases, particularly in the elderly population. Perhaps using augmented data or combining the CLIP data with other sources of information, clinical data, and others would enhance the efficiency of the model. However, it has numerous potentials in the fields of forensic and clinical dentistry, including but not limited to age estimation and identification of unidentified bodies and determination of treatment plans in orthodontists. Despite such benefits, there are ethical concerns regarding data privacy as well as the multi-step decision-making process and interpretability of the model that must be resolved to use it in clinical and forensic contexts. However, more significant and diverse data should be used to validate our finding for the full implementation of the model.

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Conflict of Interest: None

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