BULLETIN OF STOMATOLOGY AND MAXILLOFACIAL SURGERY

Volume 21, N 9

DOI:10.58240/1829006X-2025.21.9-542

ORIGINAL RESEARCH

THE ARTIFICIAL INTELLIGENCE IN DENTAL FORENSICS: AGE ESTIMATION ACCURACY COMPARED WITH MANUAL METHODS

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Received: *Sep.2 28. 2025;* ***Accepted:*** *Oct. 18, 2025;* ***Published:*** *Oct 23,2025*

ABSTRACT

Background: Age estimation has an important role in forensic sciences, with dental radiographs serving as a reliable source. Conventional methods which are widely used such as Demirjian's technique, may vary depending on examiner subjectivity. Artificial intelligence (AI) offers potential for speed and automation. This study compared the accuracy of dental age estimation using a modified Demirjian's method and ChatGPT-based AI estimation.

Methods: 50 digital orthopantomograms (25 males and 25 females, aged 10–20 years) were collected from digital OPG archives and analysed. Chronological age was calculated from the date of birth. Manual dental age estimation was estimated using the Indian modification of Demirjian's method. ChatGPT was prompted to assign tooth development stages, calculate maturity scores, and estimate age based on the OPGs uploaded. Spearman's correlation, Mann–Whitney U test, mean absolute error (MAE), and root mean square error (RMSE) were applied for statistical analysis.

Results: All age datasets showed deviation from normality (Shapiro–Wilk, $p < 0.05$). Manual dental age showed strong correlation with chronological age ($\rho = 0.871$, $p < 0.001$), at the same time AI-based estimation showed weaker correlation ($\rho = 0.394$, $p = 0.0047$). A moderate correlation was observed between manual and AI estimates ($\rho = 0.418$, $p = 0.0025$). No significant gender-based differences were found. Accuracy was higher for the manual method (MAE = 1.22 years, RMSE = 1.55 years) compared to AI (MAE = 2.92 years, RMSE = 3.66 years).

Conclusion: In this study it was found out that manual age estimation using the modified Demirjian method remains more accurate than ChatGPT based age estimation, confirming its role as the gold standard in forensic cases. While AI demonstrated speed and consistency, its current limitations are the absence of datasets. In the future AI can be trained on wide radiographic datasets so that it can be an adjunct to. conventional methods , but manual estimation method remain unavoidable at present.

Keywords:Dental age estimation, Demirjian's method, Artificial intelligence, ChatGPT, Panoramic radiography

INTRODUCTION

Age determination of unidentified human remains is crucial in crime investigations and mass disasters, as information such as age at death, date of birth, year of death, and gender can help narrow down and identify the individual from a large pool of potential matches [1]. Methods of age estimation utilize various parameters like developing dentition, skeletal development or age related changes[2,3]. Teeth are the most resilient tissue in the human body capable of withstanding extreme considerations. Teeth can provide valuable evidence including age , sex and ethnicity. When examining the skeleton of a mature individual, different methods are used to estimate the age at death during earlier stages of life—such as in a fetus, newborn, toddler, or other immature phases[4]. Age is a fundamental aspect of human identity, and in forensic science, biological age can be estimated through various indicators such as bones and teeth. Dental age estimation relies on parameters like tooth development and eruption, postformation changes, and third molar development. Numerous studies have proposed different methods for estimating dental age[5,6,7]. Dental age can be assessed using two main approaches: radiographic evaluation and clinical observation of tooth eruption. The methods are generally classified into three categories: (1) morpho-histological methods, (2) radiological methods, and (3) biochemical methods [8,9]. Traditional methods have been extensively validated across diverse populations worldwide, the introduction of automated techniques based on deep learning has enhanced both performance and practical applicability. This marks a significant advancement in the field of chronological age estimation, as these methods offer faster processing and eliminate the subjectivity associated with human observation[10]. Demirjian's method of tooth development is the most commonly used technique for estimating age in people with erupting teeth[11]. Demirjian's 1973 staging system was originally developed using specific populations like FrenchCanadian children. As a result, their accuracy often declines when applied to individuals from different ethnic or regional backgrounds, frequently leading to age overestimation or underestimation[12]. The merging of artificial intelligence into dentistry provides opportunities for enhancing diagnostic accuracy, treatment planning and improving patient care. But its application is subject to various types of bias including sampling, computational and observer bias, all of which should be addressed for reliable outcomes [13]. AI based automated systems have been introduced to eliminate examiner subjectivity in age estimation. Among these, the Deep Learning Convolutional Neural Network (CNN) approach has shown the best performance, achieving accuracy comparable to that of trained researchers. Artificial intelligence has also demonstrated significant utility in other areas of dental radiographic analysis. For instance, Subramanian et al. (2022) highlighted the effectiveness of AI-based systems in orthodontics, particularly in automating cephalometric landmark identification using CNNs.
Their review emphasizes the growing role of AI in enhancing diagnostic precision and reducing interobserver variability in dental imaging. These advancements in cephalometric analysis underscore a shared potential for AI applications across both orthodontic and forensic disciplines[14]. This study aims to evaluate and compare the accuracy of age estimation using artificial intelligence tools such as ChatGPT with traditional manual methods, using chronological age as the reference. A total of 50 orthopantomograms(OPGs), iCloud including 25 males and 25 females aged between 10 and 20 years, were analyzed. The manual method applied was the modified Demirjian's 8 teeth approach proposed by Ashish Acharya.

The purpose of this study was to determine whether ChatGPT, a form of artificial intelligence, could improve dental age estimation's objectivity and reproducibility when compared to the extensively used Demirjian's approach. Although Khanagar et al. emphasized the benefits of using AI for age estimation in order to reduce examiner bias and enhance consistency in radiograph interpretation, the majority of the research in their analysis used CNN-based models. The present study is innovative because it uses a general-purpose AI (ChatGPT) to directly perform tooth staging and age estimation using Modified Demirjian's method—a fresh approach that hasn't been documented in the literature before[15].

Amitha Mohan, Dinesh Yasothkumar. The Artificial Intelligence in Dental Forensics: Age Estimation Accuracy Compared with Manual Methods.Bulletin of Stomatology and Maxillofacial Surgery.2025;21(9)542-556 doi:10.58240/1829006X-2025.21.9-542

MATERIALS AND METHODS

Study Design and Sample

This study involved 50 digital OPG's from individuals aged 10 to 20 years. The sample included 25 males and 25 females. Inclusion criteria: availability of highresolution OPGs, complete eruption or visibility of left mandibular permanent teeth including the third molar (teeth 31 to 38), and known date of birth. OPGs with missing mandibular teeth, cases without date of birth of the patient were excluded.

Chronological Age Calculation

Chronological age was calculated by subtracting the date of birth from the date of OPG acquisition.

Manual Dental Age Estimation

Two independent evaluators, blinded by the patients' chronological ages, performed manual age estimation using the Indian version of Demirjian's method by Ashish Acharya, which includes all eight left lower teeth (31 to 38), including the third molar. Each tooth was staged (0 to 9) based on its radiographic development, using a standardized tooth development chart(Figure1).

Figure 1. Orthopantomogram illustrating the developmental staging and corresponding Modified Demirjian scores assigned to each mandibular tooth (31–38)

The respective maturity scores were derived from sex-specific scoring tables (Table 1). The scores were summed to obtain a total maturity score (S), which was substituted into the following formulas:

Table 1. Tooth development stages and corresponding maturity scores used for dental age estimation

SCORING TABLE

Maturity Scores for Females

Stage	31	32	33	34	35	36	37	38
0								6.40
1							2.57	7.74
2					2.43			8.92
3				2.56	3.43		2.65	9.31
4			2.55	3.54	3.83		4.10	10.22
5	2.58	2.65	3.15	5.09	5.75	2.58	6.51	11.04
6	3.10	4.54	5.40	6.31	6.81	3.25	8.00	12.65
7	5.02	5.40	7.19	8.09	8.70	4.25	9.13	13.77
8	6.66	7.02	9.22	9.82	10.80	6.88	11.00	14.45
9	10.61	10.89	11.99	12.29	12.79	10.94	13.84	16.65

Maturity Scores for Males

Stage	31	32	33	34	35	36	37	38
0							1.70	6.19
1					1.69		2.98	7.64
2				1.70	2.27		3.41	8.28
3			1.70	1.98	3.41		4.74	8.86
4			2.67	3.52	3.41		4.88	9.89
5	2.31	2.55	4.34	5.19	5.59	2.13	6.69	11.17
6	4.35	4.71	6.14	6.47	6.96	3.73	7.89	12.25
7	5.16	5.75	7.59	8.18	8.68	4.94	9.08	13.66
8	6.56	6.97	9.52	9.84	10.64	7.00	11.13	14.07
9	10.68	10.91	12.56	12.57	13.11	11.22	13.63	15.32

- For Males:
  Age = $27.4351-(0.0097xS^2) + (0.000089xS^3)$

- For Females:
  Age = $23.7288-(0.0088xS^2)+(0.000085xS^3)$

This research was carried out following STROBE guidelines to ensure methodological precision.

AI-Based Dental Age Estimation

The same OPGs were uploaded into ChatGPT (OpenAI), along with the reference development stages and maturity score tables. ChatGPT was first prompted to evaluate each of the eight mandibular teeth (31 to 38) and assign a developmental stage (0 to 9) by comparing with the visual reference chart. Using the provided scoring table, ChatGPT then assigned maturity scores, calculated the total maturity score (S), and finally substituted this value into the respective gender-specific regression equation to estimate dental age. Thus, the entire process — from stage assignment to age estimation — was performed by AI using the same validated method.

Data analysis

All statistical analyses and data management were performed using the Statistical Package for Social Sciences (SPSS Inc., Chicago, IL, USA) for Windows and MS-Excel[Table 2]. Normality of all the three data were assessed. A pvalue less than 0.05 was considered as statistically significant deviation from a normal distribution.

Table 2. Chronological age, manual dental age, and AI-based dental age estimations of the study participants

Sl No.	PID	CHRONOLOGICAL AGE	DENTAL AGE MANUAL	DENTAL AGE AI
M	19122138010	11	11.2	11.99
F	19122338192	18	17.8	15
F	20110573463	17	19	14.5
M	21020286659	12	13.3	12.3
F	241030377498	10	12.24	14.5

F	210719113349	13	16.7	11.8
F	210920126411	11	9.7	11.8
F	230516252979	14	15.3	17.2
M	230601257426	18	18.5	13.4
F	231026293232	17	15	19.07
M	221114211590	14	12.36	12.5
M	221217217695	10	11.4	9.8
F	230204228037	13	13.13	13.6
F	230602257754	17	19	14.4
F	230301233741	10	9.7	8
F	230304234578	15	16	13
F	230405242324	16	16	14

M	230411243716	16	18.5	13.5
M	230412243878	16	17.3	13
M	230413244091	16	18.2	14.4
M	1907027887	19	19.4	14
M	1907119955	18	18.5	14.5
F	230419245324	19	17.16	11
F	230421245787	20	20.7	13
M	230421245819	12	11.1	12
M	230606258807	19	18.5	14.9
M	230502248254	13	12.04	12
F	230503248582	17	17.8	11.5
F	230503248637	12	13.8	13

F	230610259886	18	19.07	18.6
M	230622262670	19	19.43	17.6
M	20030951559	20	19.4	17.5
M	20060355755	18	18.5	18.5
M	20091565425	20	19.4	16.5
F	231003287834	14	9.7	14.7
M	230509250642	12	10.56	9.8
M	230511251193	19	19.4	12.66
F	230511251431	12	11.96	16.24
F	230512251602	12	15.1	17.48
F	230513251919	17	14.07	25.81
M	230513251922	17	18.5	21.13

F	230513251927	20	19.07	11.3
F	230513251958	15	13.8	13.5
F	230513252095	17	18	12
F	230515252313	17	19.07	13
M	230617261909	18	16.68	15.3
M	230524255365	10	10.3	10
M	230527256096	15	14.6	14
M	230601257426	18	18.5	16
M	240325324897	19	19.43	17.4

Since it showed non-normal distribution of the data, non-parametric statistical tests were employed: Spearman's rank coefficient (ρ) was done to assess the strength and direction of associations between chronological and manual dental age, chronological and AI predicted dental age, manual and AI based dent al age estimated. Mann-Whitney U test was done to assess whether any statistically significant differences in dental age estimation based on gender for both manual and AI methods. Mean Absolute Error(MAE) and Root Mean Square Error(RMSE) were performed to compare the performance of manual and AI based age estimation methods against chronological age.

RESULTS

Normality of Data

The Shapiro-Wilk test demonstrated that the distribution of chronological age (W=0.922,p=0.0028), manual dental age (W=0.890, p=0.0059) significantly deviated from normality. Therefore non-parametric statistical methods were

used for further analysis.

Correlation Between Methods

A moderate positive correlation was observed between manual and AI-based dental age estimates (Spearman's ρ = 0.418, p = 0.0025), indicating partial agreement between the two approaches .

Correlation with Chronological Age

The manual method shows a strong positive correlation with chronological age (ρ=0.0871, p<0.001) and the AI method (Figure2) showed a weaker yet statistically significant correlation(ρ=0.394,p=0.0047). This suggests that manual estimation closely aligns with the actual age (Figure 3).

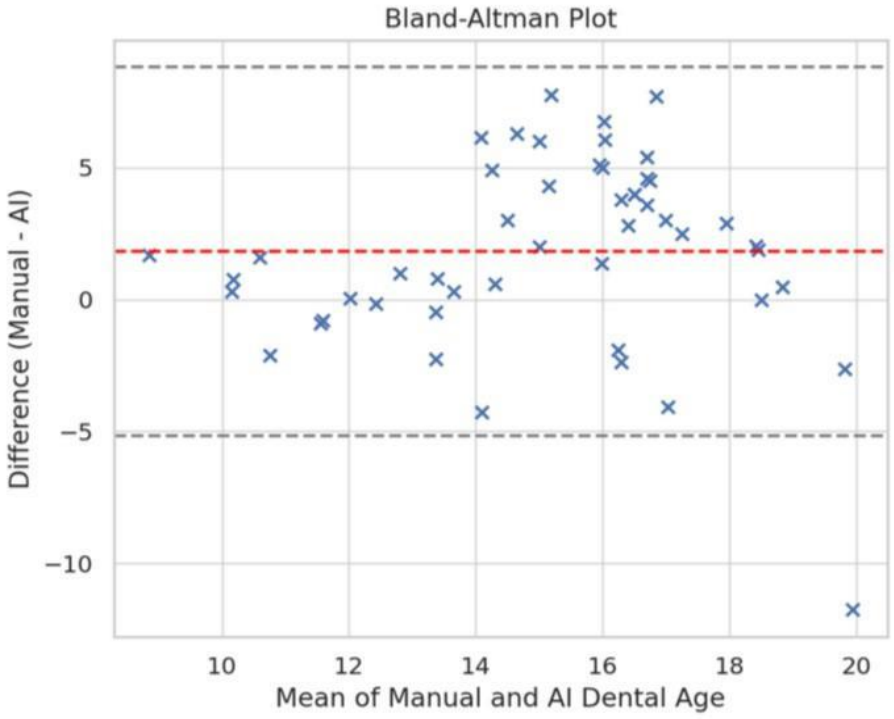

Figure 2. Bland–Altman plot illustrating the agreement between chronological age and estimated dental age using manual and AI-based methods.

Gender-Based Differences

There was no statistically significant difference in dental age estimates between male and female subjects using either method:

Manual method: Mann–Whitney U = 310.0, p = 0.8488
AI method: Mann–Whitney U = 319.5, p = 0.7037

Accuracy of Estimations

Accuracy was assessed using MAE and RMSE:

This suggests that manual estimation closely aligns with the actual age (Figure 3)

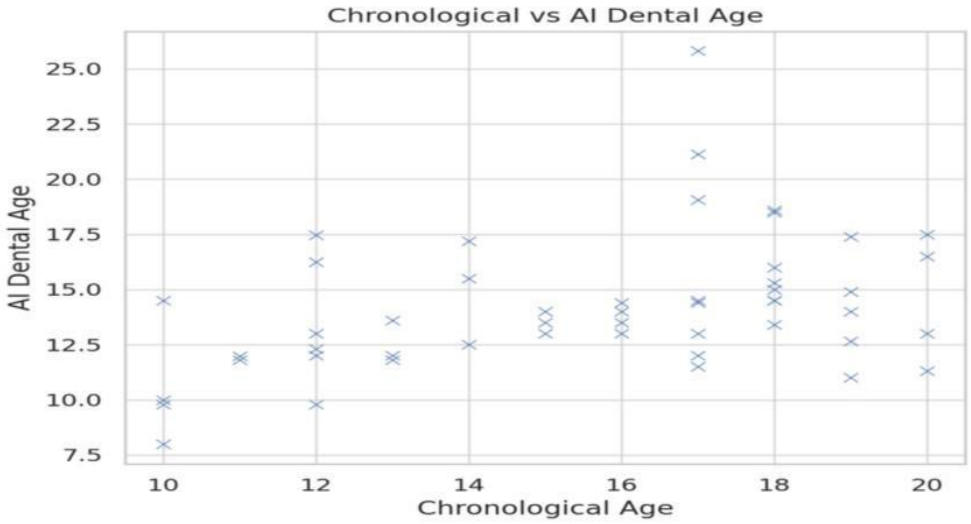

Figure 3. Scatter plot showing the correlation between chronological age and AI-predicted dental age among study participants

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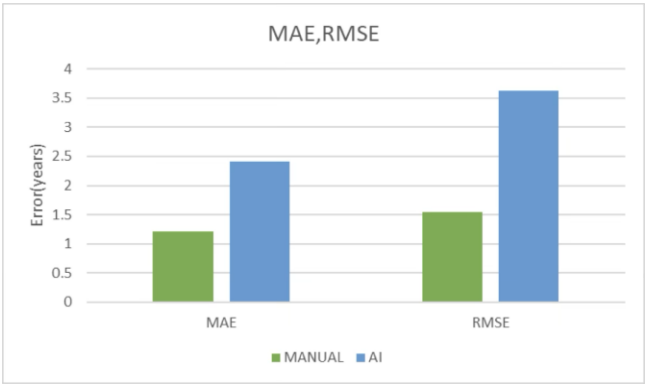

Figure 4. Bar chart illustrating the MAE and RMSE values for manual and AI-based dental age estimation methods

The manual method demonstrated significantly lower error values, indicating higher accuracy in estimating chronological age compared to the AI-based approach (Figure 4).

Scatter Plot Observations

AI tends to over and underestimate ages, reducing precision. Whereas the manual method showed much closer alignment. This indicates manual estimation method is reliable and precise compared to AI based prediction.

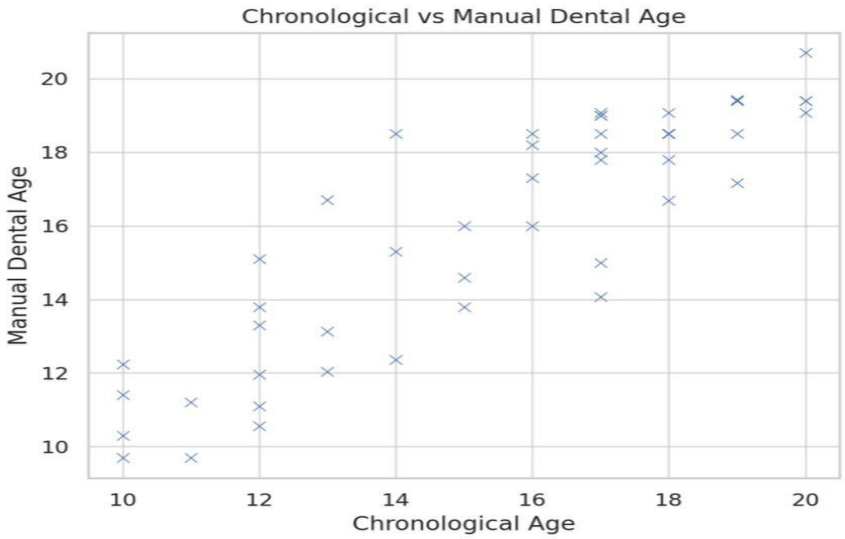

Figure 5. Scatter plot showing the correlation between chronological age and manually calculated dental age among study participants.

DISCUSSION

Anthropometry holds significant importance in human identification and serves a crucial role in medico-legal investigations related to death. Age estimation is a key part of anthropometric studies and helps identify individuals by their age in situations like legal cases, research studies, medical treatments, and other health-related evaluations. Radiographic imaging plays a vital role in forensic odontology for identifying individuals[16]. Another commonly used method for estimating age involves assessing skeletal maturity and bone age through the evaluation of cervical vertebrae, which has been well established in research[17]. Using dental developmental stages, particularly calcification stages seen on radiographs, is currently the most reliable and efficient approach for estimating age in children and adolescents, especially when documentation is absent. It also advocates for an integrated, method-combined strategy to improve precision[18].

Arumugam et al (2020) describes several standardized dental techniques used to estimate age, especially in infants and adolescents, in her review article "Different Dental Aging Charts or Atlas Methods Used for Age Estimation." These methods mainly depend on the predictable sequence of tooth development and calcification stages. Demirjian's method that uses radiographic staging of tooth development , Nolla's method that divides stages based on crown initiation to apex closure and Moorrees' method that analysed 13 stages for single rooted and 14 for multi-rooted teeth are few of various methods for age estimation[19].

The research conducted by Boraiah Shivakumar and colleagues shows a strong link between dental age and chronological age, confirming the use of Demirjian's 8 teeth method in the Indian population. This modified technique yields accurate results with minimal

discrepancies [20]. The primary objective of this study was to evaluate and compare the accuracy of dental age estimation using ChatGPT with that of the manually applied modified Demirjian's method. The findings revealed that manual estimation more closely matched the chronological age in individuals aged 10 to 20 years, indicating that conventional techniques currently provide greater accuracy within this age range. Although AI tools like ChatGPT demonstrate potential in supporting dental age assessment by delivering quick and consistent evaluations, they are not yet a substitute for the knowledge and clinical judgment of experienced pathologists or forensic experts. AI should be regarded as an adjunctive tool that complements, rather than replaces, professional expertise.

The present study found that manual dental age estimation methods outperformed AI-based models, with MAE of 1.22 years and a RMSE of 1.55 years for the manual approach, compared to a substantially higher MAE of 2.92 years and RMSE of 3.66 years for the AI-based method. These results contrast with the findings reported by Kumagai et al., where conventional methods also showed slightly better accuracy than AI models, but the differences were minimal—MAE differences of only 0.21 years and RMSE differences of less than 0.24 years (equivalent to 44–77 days and 62–88 days, respectively). Despite these differences in magnitude, both studies share key similarities: they consistently demonstrate the superior performance of manual methods over AI and utilize comparable evaluation metrics (MAE and RMSE)[21]. These observations are further supported by the systematic review conducted by Vila-Blanco et al. (2023), which examined a wide range of traditional and AI-based approaches. While AI models, particularly CNNs, showed promising results in specific age groups (notably under 15 years), their accuracy tended to decline across broader age ranges, with reported MAEs reaching up to 2.84 years. The consistently strong performance of traditional methods such as Demirjian and Cameriere, noted across all three studies, underscores their reliability, reproducibility, and interpretability. The relatively poor AI performance in the present study, especially when compared to more favorable AI results in Vila-Blanco's review, may be attributed to factors such as dataset size, image quality, population variability, or differences in model training architecture [22]. The results of this study are further supported by a study conducted in the Turkish pediatric population that compared a deep learning-based methodology with conventional approaches, such as Willems, Cameriere-European, and London Atlas. The study showed that the traditional methods demonstrated high intraclass correlation coefficients (ICCs) ranging from 0.92 to 0.95, while the deep learning model showed a slightly lower ICC of 0.89. The performance of AI was close to that of manual methods in their dataset; the discrepancy observed in the present study where AI demonstrated significantly higher error implies that the efficiency of AI-based models may vary considerably depending on factors such as model architecture, population characteristics, and dataset quality. These differences highlight the current limitations of AI in this field. Research consistently shows that traditional dental age estimation methods are reliable, repeatable, and dependable, emphasising their relevance in both forensic and clinical applications [23]. In contrast, the study by Han et al. (2022) comparing the performance of manual, semiautomated, and fully automated dental age estimation models using panoramic radiographs showed that a fully automated deep learning model (ADAE), operating without any human input, showed a low MAE of 0.83 years, approximately half that of traditional manual estimation (MAE ≈ 1.66 years). Their ADSE which utilized manually defined features, produced an MAE of 1.63 years, closely aligning with manual outcomes. These results differ from those of the present study, where manual estimation ($MAE = 1.22$; $RMSE = 1.55$) significantly outperformed the AI-based model ($MAE = 2.92$; $RMSE = 3.66$). The heterogeneity in outcomes could be due to variations in AI model design, dataset characteristics, image quality, and differences in participant demographics [24]. The study by Koch et al. (2025) introduced a deep learning model for forensic age estimation using a dataset of 21,814 orthopantomograms from individuals aged 1 to 25 years. Their custom CNN, trained extensively over 1,000 epochs, demonstrated strong predictive accuracy on an independent test set of 1,814 images, achieving a MAE of 0.93 ± 0.81 years and a mean signed error

(MSE) of –0.06 ± 1.23 years. 63% of the AI-based age predictions fell within one year of the actual age, and 95% were within 2.5 years. These results reinforce the significance of AI-based systems when developed using large, high-quality datasets and optimized architectures. In contrast, the AI model employed in the present study demonstrated significantly lower accuracy, with an MAE of 2.92 years and an RMSE of 3.66 years, highlighting the impact of factors such as smaller dataset size, image resolution, and model learning accuracy on AI performance. While Koch et al.'s findings demonstrate that AI has the potential to outperform traditional methods under ideal circumstances, the current results validate the dependability of manual approaches in practical and resource-limited settings. Though combined results of several studies indicate that although AI models can perform better than manual estimation in ideal circumstances, conventional techniques are still more dependable in situations where AI systems are limited by inaccurate training protocols, lack of imaging quality , or a lack of data [25].

LIMITATIONS AND FUTURE SCOPE

The diversity of the population might not have been suitably reflected by the small sample size of 50 OPGs in this research. The AI tool employed (ChatGPT) is a general-purpose model, not one that is particularly trained on dental radiographs; this constrained its ability to properly analyze imaging features. The research only investigated one ethnic group and age group (10–20 years), thereby limiting the relevance of the conclusions to other populations and age ranges. Moreover, the only comparison was the modified Demirjian's method; adding other proven methods might provide a more thorough assessment.

Future research should focus on directly training artificial intelligence models on large, labeled radiographic datasets to improve accuracy and flexibility. More complete results would come from comparative studies including a range of populations, wider age ranges, and many approaches for estimating dental age. Incorporation of multimodal data, including skeletal and biochemical markers, will help artificial intelligence models become more reliable. The development of understandable, specific AI systems has the potential to eventually complement expert-driven techniques and promote the general application of such systems in clinical and forensic contexts.

CONCLUSION

This study provides a comparative analysis of dental age estimation accuracy using a widely accepted manual method and an AI-based approach, ChatGPT for the evaluation of orthopantomograms in individuals aged 10 to 20 years. Manual age estimation, based on the modified Demirjian method, was significantly more accu rate, with lower MAE and RMSE values compared to the AI-based model. These results are in line with other recent studies that support the accuracy and dependability of traditional techniques, specifically in forensic and clinical context. Although AI tools like ChatGPT offer the advantage of speed and automation, their performance is currently limited by factors such as lack of imagetrained data, reliance on text-based inference, and absence of direct feature learning from radiographs. In contrast, deep learning models trained on large, annotated datasets have shown promising results, indicating that with further refinement and validation, AI has the potential to complement or even surpass manual approaches in select scenarios. Nonetheless, until such models are widely validated and standardized, manual methods remain the gold standard in dental age estimation. The present findings underscore the importance of maintaining expertdriven techniques while continuing to explore AI advancements that could improve objectivity, efficiency, and scalability in forensic dental practice.

DECLARATIONS

Ethics approval and consent to participate

Not applicable

Conflicts Of Interests

None

Funding

None

LIST OF ABBREVIATIONS

ADAE – Automated Dental Age Estimation

ADSE – Automated Dental Stage Estimation

AI – Artificial Intelligence

CNN – Convolutional Neural Network

ICC – Intraclass Correlation Coefficient

MAE – Mean Absolute Error

MSE – Mean Signed Error

OPG – Orthopantomogram

REFERENCES

1.Alkass K, Buchholz BA, Ohtani S, Yamamoto T, Druid H, Spalding KL. Age estimation in forensic sciences: application of combined aspartic acid racemization and radiocarbon analysis. Mol Cell Proteomics. 2010 May;9(5):1022-30. doi: 10.1074/mcp.M900525-MCP200. Epub 2009 Dec 4.

2,Moraitis K, Zorba E, Eliopoulos C, Fox SC. A test of the revised auricular surface aging method on a modern European population. J Forensic Sci. 2014 Jan;59(1):188-94. doi: 10.1111/1556-4029.12303.

3.Priya E. Methods of skeletal age estimation used by forensic anthropologists in adults: a review. Forensic Res Criminol Int J. 2017;4(2):41-51. DOI: 10.15406/frcij.2017.04.00104

4.S. S and A. Arthanari, "Age Estimation Using Demirjian Eight Teeth Method In Maxillary Left Molar and Mandibular Left Molar In Indian Population," 2023 International Conference on Business Analytics for Technology and Security (ICBATS), Dubai, United Arab Emirates, 2023, 1-6, doi: 10.1109/ICBATS57792.2023.10111468.

5.Kurniawan A., Agitha S. R. A., Margaretha M. S., et al. The applicability of Willems dental age estimation method for Indonesian children population in Surabaya. Egyptian Journal of Food Science.2020;10(1)doi:10.1186/s41935-020-0179-6.

6.Ruth M. S. M. A., Novita G. L., Gita L., Kurniawan A., Utomo H. Age estimation with smartphone: is it reliable for forensics identification? Dentika: Dental Journal<2020;23(2):34–38.doi: 10.32734/dentika.v23i2.4494.

7.Kurniawan A, Chusida A, Atika N, Gianosa TK, Solikhin MD, Margaretha MS, Utomo H, Marini MI, Rizky BN, Prakoeswa BFWR, Alias A, Marya A. The Applicable Dental Age Estimation Methods for Children and Adolescents in Indonesia. Int J Dent. 2022 Feb 15;2022:6761476. doi: 10.1155/2022/6761476.

8.Manjunatha BS, Soni NK. Estimation of age from development and eruption of teeth. J Forensic Dent Sci. 2014 May;6(2):73-6. doi: 10.4103/0975-1475.132526

9.Verma M, Verma N, Sharma R, Sharma A. Dental age estimation methods in adult dentitions: An overview. J Forensic Dent Sci. 2019 May-Aug;11(2):57-63. doi: 10.4103/jfo.jfds_64_19.

10.Vila-Blanco N, Varas-Quintana P, Tomás I, Carreira MJ. A systematic overview of dental methods for age assessment in living individuals: from traditional to artificial intelligence-based approaches. Int J Legal Med. 2023 Jul;137(4):1117-1146. doi: 10.1007/s00414-023-02960-z.

11.G. S. Sutharshan and A. Arthanari, "Age Estimation Using Demirjian's 8 Teeth Method Maximillary Upper Right Third Molar," 2023 International Conference on Business Analytics for Technology and Security (ICBATS), Dubai, United Arab Emirates, 2023, 1-4, doi: 10.1109/ICBATS57792.2023.10111228.

12. Bérgamo AL, de Queiroz CL, Sakamoto HE, Alves da Silva RH (2016) Dental Age Estimation Methods in

Forensic Dentistry: Literature Review. Forensic Sci Today 2(1): 004-009. DOI: 10.17352/fst.000005

13.Royapuram Parthasarathy P, Patil SR, Dawasaz AA, Hamid Baig FA, Karobari MI. Unlocking the Potential: Investigating Dental Practitioners' Willingness to
Embrace Artificial Intelligence in Dental Practice. Cureus.2024;16(2):e55107.doi: 10.7759/cureus.55107.

14. Khanagar SB, Albalawi F, Alshehri A, Awawdeh M, Iyer K, Alsomaie B, Aldhebaib A, Singh OG, Alfadley A. Performance of Artificial Intelligence Models Designed for Automated Estimation of Age Using Dento-Maxillofacial Radiographs-A Systematic Review. Diagnostics (Basel). 2024 May 22;14(11):1079. doi: 10.3390/diagnostics14111079.

15.Subramanian AK, Chen Y, Almalki A, Sivamurthy G, Kafle D. Cephalometric Analysis in Orthodontics Using Artificial Intelligence-A Comprehensive Review. Biomed Res Int. 2022 Jun 16;2022:1880113. doi: 10.1155/2022/1880113.

16.Subasree S, Dharman S. Age and gender determination using maxillary sinus and sella turcica in forensics-A lateral cephalometric study. Indian Journal of Forensic Medicine & Toxicology. 2019;13(4):151-7.

17.Chandrasekar, R., Chandrasekhar, S., Sundari, K.K.S. et al. Development and validation of a formula for objective assessment of cervical vertebral bone age. Prog Orthod. 21, 38 (2020). https://doi.org/10.1186/s40510-020-00338-0]

18.Singhal, Ishita; Dave, Aparna; Arora, Manpreet; Rai, Radhika; Saluja, Pulin. A Review on Dental Age Estimation in Children and Adolescents. Journal of Forensic Science and Medicine 10(3):p 220-233, Jul–Sep 2024. | DOI: 10.4103/jfsm.jfsm_46_23

19.Arumugam, Vidhya & Doggalli, D Nagabhushana. (2020). Different Dental Aging Charts or Atlas Methods Used for Age Estimation–A Review. Asian Journal of Basic Science & Research. 02. 64-74. 10.38177/AJBSR.2020.2306.

20.Shivakumar B, Arunakshi, Niveditha, Shivaprasad, Manjuprasad. Validation of demirjian's 8-teeth method of age estimation in the population of Bengaluru. J Oral Maxillofac Pathol. 2021 Sep-Dec;25(3):499-502. doi: 10.4103/jomfp.JOMFP_330_20. Epub 2022 Jan 11.

21.Kumagai, A.; Jeong, S.; Kim, D.; Kong, H.-J.; Oh, S.; Lee, S.-S. Validation of Data Mining Models by Comparing with Conventional Methods for Dental Age Estimation in Korean Juveniles and Young Adults. Sci. Rep. 2023, 13, 726.

22. Vila-Blanco N, Varas-Quintana P, Tomás I, Carreira MJ. A systematic overview of dental methods for age assessment in living individuals: from traditional to artificial intelligence-based approaches. Int J Legal Med. 2023 Jul;137(4):11171146. doi: 10.1007/s00414-023-02960-z.

23.Yavuz, B.S., Ekmekcioglu, O. & Ankarali, H. Comparison of different dental age estimation methods with deep learning: Willems, CamerereEuropean, London Atlas. Int J Legal Med 139, 1661– 1672 (2025). https://doi.org/10.1007/s00414-02503452-y

24. Han, Mengqi & Du, Shaoyi & Ge, Yuyan & Zhang, Dong & Chi, Yuting & Long, Hong & Yang, Jing & Yang, Yang & Xin, Jingmin & Chen, Teng & Zheng, Nanning & Guo, Yucheng. (2022). With or without human interference for precise age estimation based on machine learning?. International Journal of Legal Medicine. 136. 821-831.10.1007/s00414-02202796-z.

25..Koch, Rahel & Mentzel, Hans-Joachim & Heinrich, Andreas. (2025). Deep learning for forensic age estimation using orthopantomograms in children, adolescents, and young adults. European Radiology. 35. 10.1007/s00330-025-11373-y.