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Dental Radiography in Age Determination: Contemporary Methods and Trends

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Abstract

The determination of an individual's age assumes paramount significance in forensic and legal contexts, necessitating the utilization of diverse techniques. Dental radiography emerges as a non-invasive approach for determining age-related dental changes. This method grants a comprehensive analysis of various dental features to identify an individual's precise age, place them within designated age ranges, or define whether they exceed or subordinate to specific age thresholds. This review summarizes age estimation methodologies using dental radiography and conducts the investigations into contemporary trends by reviewing relevant studies published in Pubmed between 2020 and 2023. Age categorization delineates into three distinct phases: pre-natal, neo-natal, and post-natal; childhood and adolescence; and adulthood. Panoramic radiography becomes the predominant radiographic modality, with the Demirjian method is more commonly known for age estimation in the initial two phases. In contrast, adulthood age estimation relies on anatomical changes. Significantly, artificial intelligence (AI) technology has recently attracted attention for age estimation, yielding promising results. AI demonstrates the potential to enhance the accuracy of conventional methodologies, diminishing human errors and mitigating associated workload burdens, offering inventive ground for future advancements.

Keywords: age estimation, dental imaging, dental radiography, forensic dentistry, forensic odontology

Introduction

Age estimation holds significant importance in both forensic and legal contexts. Numerous methods are employed for this purpose, involving various anatomical markers such as cranial suture closure, pubic symphysis, auricular surface, lumbar vertebrae, acetabulum, bone histomorphometry, and teeth. Among these, teeth stand out as remarkably durable components of the human body, often remaining well-preserved even after disasters or accidents. Their resilience makes them invaluable for post-incident investigations.(1-3) Age estimation from dental structures encompasses three distinct categories: morphological methods, such as assessing tooth wear(4-6) and root transparency; biochemical methods, including examining aspartic acid racemization and other amino acids within the tooth(7-9), and radiological methods, including evaluating tooth development and eruption(6,10-20), and analyzing pulp size regression due to secondary dentin formation.(6,21-32) Dental radiography has emerged as a practical, non-destructive technique that significantly aids age estimation.(6,10-18,21-23,25-33) It is essential to acknowledge that bone and teeth growth rates exhibit variations based on nationality. Employing methods that utilize population-specific databases enhances accuracy in age estimation.(10-13,16,19,25,29-32)

Additionally, many age estimation models have been manually developed, introducing the potential for human error.(4,5,10-19,21,22,25,33,34) Addressing this limitation, artificial intelligence (AI) has become a promising approach for creating new age estimation models, as evidenced by previous studies.(6,20,23,35,36) Deep learning, in particular, has gained prominence in age estimation due to its capacity to reduce human workload, enhance accuracy in detection and decision-making, and, in some cases, even classify genders as part of the age estimation process.(6,20,35-37)

This review article is to provide a comprehensive overview and critically assess recent trends in age estimation methodologies through the application of dental radiography.

Dental radiography in age estimation

Age estimation stands as a fundamental procedure within the domain of medico-legal investigations. Historical evidence reveals that in the early 19th century, teeth served as pivotal indicators of age, particularly in relation to child labor regulations. Notably, the English Parliament of 1837 implemented the "Teeth A Test of Age," stipulating that children under the age of nine were prohibited from employment, while those between nine and twelve years old faced restricted working hours based on dental observations related to tooth eruption.(38)

Furthermore, the utilization of dental structures for age estimation has gained prominence due to their exceptional durability.(1-3) Situated within the protective confines of the oral cavity, teeth remain shielded from external environmental factors. Consequently, they exhibit a remarkable resistance to deterioration and a capacity for long-term preservation, establishing them as invaluable assets for age determination in the domains of forensic science, anthropology, and archaeology.

Dental radiography serves as a widely employed, non-invasive methodology for the examination age-related changes within teeth. This involving technique includes various modalities such as intraoral radiography (periapical radiograph), orthopantomography (OPG), cone-beam computed tomography (CBCT), and magnetic resonance imaging (MRI). The non-invasive tooth-based age estimation techniques enhance their appeal, as they eliminate the need for invasive procedures, thereby ensuring minimal disruption to samples and the preservation of invaluable remains.

The process of ascertaining an individual's age through radiological examination involves a comprehensive assessment of multiple features. These encircle the development and mineralization of tooth follicles, root resorption, and completion, and secondary dentin deposition within the pulp cavity. The outcome of this method varies, depending on the specific approach employed, ranging from the estimation of an individual's age, the classification into age groups to the determination of whether an individual falls below or above a precise age cut-off. Age can be stratified into three primary phases based on an individual's age range: pre-natal, neo-natal, and post-natal phase; children and adolescence phase; and adult and elderly phase. Chronological progression of age estimation methods across three age phases is shown in Figure 1 and described in details as follows:

1. Pre-natal, neo-natal, and post-natal phase

The initiation of primary incisor mineralization occurs during the 16th week of intrauterine development.

Prior to the tooth germs mineralization, it is discernible as a radiolucent area in the radiographic images. Subsequently, during the prenatal phase of fetal development, the mineralization of primary teeth manifests as radiopaque structures resembling teeth within radiographs.(39)

In 1965, Kraus and Jordan(40) reported the early mineralization of primary teeth and the permanent first molar. This framework comprises ten stages, denoted by Roman numerals I to X, with stage IX further subdivided into three sub-stages and stage X into five sub-stages. This approach, known as the "tooth atlas method," is valuable for age estimation during this developmental phase.

2. Children and Adolescents phase

Age estimation through the observation of tooth development has been widely employed for assessing the age of children and adolescents. This estimation is facilitated through clinical examination and dental radiography, advantaging the precise and stable nature of tooth development. Several methods have been elucidated as follows:

2.1 Tooth development staging method

In 1960, Nolla proposed a method that relies on the observation of calcification in permanent teeth to estimate age. This method involves dividing tooth development into ten stages, including seven maxillary and mandibular teeth on the left side, from the absence of a crypt to complete root formation.(41) The cumulative stages of all teeth provide an estimated age. In 1973, the method of Demirjian in the tooth development staging method was introduced.(42) and then in 1976, Demirjian delivered an age estimation method based on the development of seven lower left permanent teeth from the left lower central incisor to the second molar, visible in panoramic radiographs.(43) This method presents percentile standards for ages ranging from 2.5 to 17.0 years, separately for each gender. It involves eight stages, denoted A to H, representing the progression from tooth mineralization to the completion of development. Subsequent studies, such as Willems *et al.*(44), have adapted and modified the Demirjian method to suit their populations. Additionally, many studies have utilized the developmental stage proposed by Demirjian *et al*. to assess the development of third molars and other selected teeth, combined with chronological age, to formulate regression formulas for age estimation.(10,19,45)

2.2 Atlas of human tooth development and eruption method

The development and eruption of primary and permanent teeth can be assessed through panoramic radiographs, serving as valuable age estimation indicators. The widely used London Atlas by AlQahtani(18) comprehensively illustrates tooth growth and emergence, covering the entire range from ages 1 to 23, including the in-utero period from 30 weeks to birth. Various studies have explored the applicability of this method in their respective populations, yielding promising results.(46-48)

2.3 Open apices measurement method (Cameriere method)

In 2006, Cameriere introduced an age estimation method centered on measuring open apices of seven mandibular left permanent teeth, ranging from the left mandibular central incisor to the second molar. This method revealed significant and negative correlations between age and open apices in teeth. Additionally, gender and the number of teeth with completely closed root canal apical ends (N0) exhibited significant correlations with chronological age. Utilization of a stepwise multiple regression model, it was demonstrated that a linear relationship exists between open apices, N0, and age.(49)

In instances where the roots of all seven permanent teeth roots are fully closed, attention turns to the third molars, the last teeth to develop. Some studies have indicated that the complete development of third molars can serve as an indicator of adulthood or minority status.(50-53) One notable method in this context is the Third molar maturity index (I3M) proposed by Cameriere.(50) This index proves valuable in legal contexts to ascertain whether an individual has reached the age of maturity, typically set at 18 years. It is based on the relationship between chronological age and the I3M, defined as the ratio between the sum of two apical pulp widths measured from the inner sides of two open apices and tooth length. If the root development of the third molars is complete, I3M = 0, indicating that the individual is at least 18 years old; otherwise, if I3M < 0.08, they are classified as below 18 years old, based on the results of a logistic model.(50)

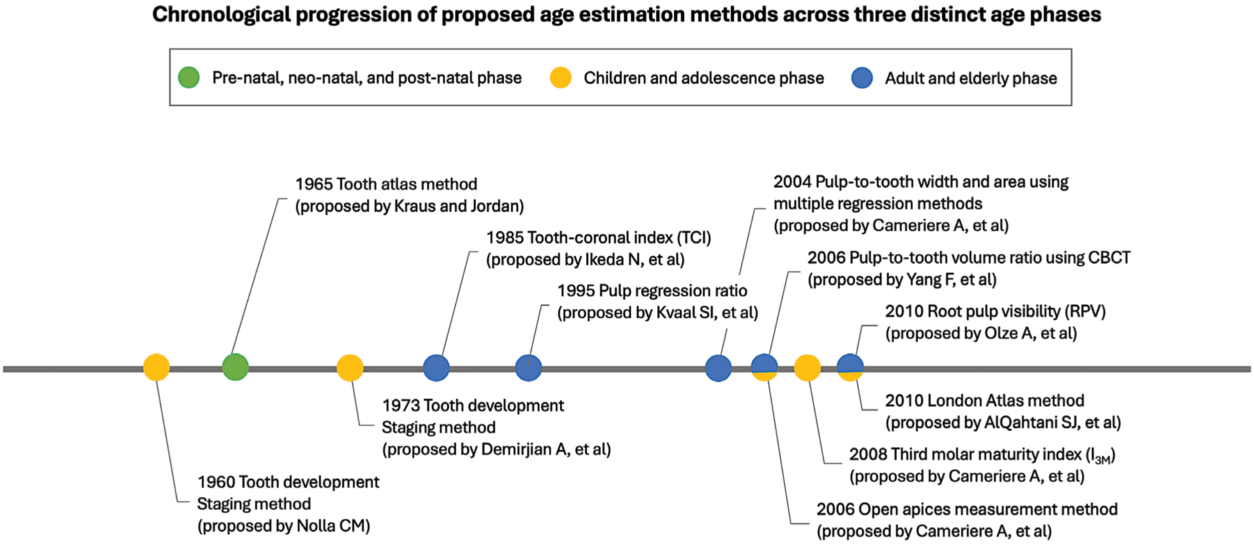

Figure 1: Chronological evolution of proposed age estimation methods across three distinct age phases: prenatal, neo-natal, and post-natal stages; childhood and adolescence stages; and adulthood stages.

3. Adult and elderly phase

3.1 Pulp regression ratio

Age estimation during late adolescence and adulthood presents challenges due to the intricate nature of fully developed permanent teeth. Estimating age based on tooth development in this age group can be inherently challenging or unavailable. Therefore, the assessment of adult age often relies on the examination of changes in secondary dentin. As individuals age, dentin thickens due to the continuous formation of secondary dentin, resulting in a reduction in the pulp cavity size. This correlation between age and the pulp regression ratio serves as a useful tool for estimating age within a specific range.(27,54,55)

3.2 Linear measurement and ratio

The Kvaal method(27) involves the examination of pulp/root length, pulp/tooth length, and pulp/root width, which have shown associations with chronological age. Ratios were calculated to account for potential film distortion at three distinct levels. Regression analysis of these ratios was performed to develop an age estimation formula. This method is particularly valuable for assessing the age of individuals with single-rooted teeth, including the maxillary central incisor, maxillary lateral incisor, maxillary second premolar, mandibular lateral incisor, mandibular canine, and mandibular first premolar. Some studies also incorporate additional teeth, such as the maxillary canine, due to its extensive root length and minimal likelihood of being missing.(29,32)

Additionally, the tooth-coronal index (TCI) or coronal pulp cavity index is a widely exploited method that examines the relationship between secondary dentin deposition and age, similar to the Kvaal method. However, TCI calculations are limited to the crown area.(54,55) The TCI, proposed by Ikeda *et al.*(54), is determined by measuring the coronal height (CH), defined as the maximum perpendicular distance from the cervical line to the tip of the highest cusp of the tooth. The coronal pulp cavity height (CPCH) denotes the distance from the cervical line to the coronal tip of the pulp chamber. TCI is expressed by (CPCH×100)/CH and is analyzed for each tooth, with regression against actual age yielding an age estimation model. Precision in TCI assessment hinges on the accurate identification of reference points, including the cervical line and the mesial and distal cementoenamel junction points, which demarcate the division between the crown and root.(54,55)

3.3 Volumetric measurement and ratio

In 2004, Cameriere introduced an age estimation method that relies on the observation of the relationship between pulp and tooth dimensions in single-rooted teeth in panoramic radiographs. This method utilizes ratios such as pulp-tooth width, length ratio, and area ratio, pulp-to-root ratio, and tooth length. A multiple regression model revealed a linear relationship between the pulp-to-root width at the mid-level of root and age, as well as between the pulp-to-tooth area and chronological age.(56)

Subsequently, various studies have explored the assessment of changes in pulp cavity volume using ground truth data obtained through various radiographic techniques, including CBCT, which offers enhanced accuracy. Yang *et al.*[57] reported the examination of the relationship between pulp-to-tooth volume ratio and age using CBCT scans of single-rooted teeth. Customized voxel counting software was utilized, revealing a linear relationship between the pulp-to-tooth volume ratio and age.[57] However, correlations may vary across different genders and populations, emphasizing the importance of utilizing population-specific databases.[58-60]

3.4 Root pulp visibility (RPV)

Following the completion of tooth formation, the continuous deposition of secondary dentin gradually narrows the pulp canal lumen. This knowledge underpins an age estimation method that assesses the visibility of pulp in radiographic images.

In 2010, Olze *et al.* introduced an age estimation method that focuses on the observation of pulp visibility in fully formed mandibular third molars with apical closure. This method categorizes individuals into four stages based on the visibility of the pulp lumen within the root canals. In Stage 0, the lumen of all root canals is visible to the apex. In Stage 1, the lumen of one root canal is partially obscured. In Stage 2, the lumen of two root canals is partially obscured, or one canal may be virtually invisible its entire length. In Stage 3, the lumen of two root canals is virtually invisible throughout their entire lengths. The study results indicate uncertainty regarding whether the method can accurately determine if someone is younger than 18 when in Stage 0. However, individuals in Stages 1, 2, or 3 were all found to be at least 21 years old.[61]

Artificial intelligence aids the age estimation process.

It has become evident that many age estimation models are susceptible to human error, primarily owing to human interpretation, which can introduce variability and bias. However, this challenge finds resolution through the application of automated AI methodologies for the development of novel age estimation models. AI has the capacity to minimize human error and reduce subjectivity in age estimation. It employs standardized algorithms, enhancing the consistency and reliability of age estimations by evaluating a multitude of dental features, from tooth development stages to anatomical changes, facilitating more precise age predictions. Prior investigations have demonstrated the efficacy of AI-powered age estimation models, guiding in several advantages, including significant cost and resource savings.[20,62]

While AI assistance in age estimation predominantly revolves around binary or multiple-group age classification, a lesser number of models aspire to achieve numeric age regression. Deep learning has garnered prominence in the ground of age estimation due to its capacity to minimize human intervention while simultaneously enhancing accuracy in the processes of detection and decision-making. Certain studies have exploited deep learning further to classify genders within the context of age estimation.

Numerous studies have embraced fully automatic, deep-learning-based solutions offering two significant advantages. Firstly, these methods require annotation exclusively in terms of expected age, thus reducing the time investment as the traditional process in dental age estimation is mostly manually done and allowing the utilization of expansive datasets comprising thousands of images. Secondly, these approaches circumvent the need for expert identification of specific teeth and bone structures, instead relying on image components that the algorithm deems most relevant to the task at hand.[63] Notably, these automatic methodologies maintain functionality even in scenarios involving missing teeth. While these automatic techniques have elevated the performance and utility of dental age estimation methods, there exists room for enhancement in their validation.

The relatively recent emergence of deep learning techniques implies that the automatic methodologies have yet to undergo comprehensive testing across diverse populations or acquisition devices beyond their original contexts. This imparts a degree of uncertainty regarding their generalizability to varied scenarios. Nevertheless, the versatility of these methods enables simplistic adaptation to distinct situations through the employment of specialized domain adaptation techniques, such as transfer learning or fine-tuning.[64]

Current trends of the Radiology-based age estimation

A review of studies published in the Pubmed database in last three-year (2020-2023) was conducted to find the contemporary trends in age estimation via radiology. The search incorporated the MeSH term "Age Determination by Teeth*/methods" (81 studies) and relevant terms related to dental, age estimation, and radiography, connected with the Boolean operator "AND" (134 studies). The review exclusively considered articles published in English, full-text-accessibility and the usage of human radiography. The 215 collected data on 26 October 2023 included title, author information, year of publication, and full papers. With duplicates excluded (60 studies), 155 selected results adhered to specific criteria: age estimation utilizing dental or periodontal tissue, with a focus on human radiography specific to the dentition, with reviews and reports excluded. 84 studies were excluded due to the criteria, in total, 71 studies underwent thorough assessment.(6,23,32,45,47,48,65-129) The publication count being at its highest in 2022 and following by in 2021 and 2020. Furthermore, the objective was to locate the most recent trend studies, which prompted the inclusion of studies up to 2023.

OPGs emerged as the most frequently used radiographic modality. Its popularity stems from its user-friendly nature, data collection simplicity, and ability to capture multiple teeth and anatomical changes within a single image. Consequently, numerous age estimation methods, such as the staging method, atlas, and assessment of open apices, rely greatly on OPG. Additionally, CBCT has proven valuable for assessing tooth volume, pulp cavities, and open apices. However, its applicability for evaluating developmental stages remains a topic of discussion. A study reported the use of MRI to examine pulp tissue areas and revealed the potential of MRI segmentation of tooth tissue volumes in predicting age for populations over 18 years old.(116) In this context, 9.4 tesla ultra-short echo time (UTE)-MRI is considered a suitable option for both single-rooted and multiple-rooted teeth(75,90), offering robust reliability and lower variation compared to CBCT. Nonetheless, manual segmentation is requisite for MRI due to the necessity for a detailed interior representation of the pulp cavity.(90) A study utilized periapical radiography for dental age estimation using the pulp and tooth ratio method with excellent results.(32)

The distribution of age estimation methods is depicted in Figure 2, with further details available in Tables 1-3. The review denotes the continued prevalence of age estimation rooted in tooth development, accounting for 59% of all results. This preference arises from the method's precision in tracking developmental timelines, thereby mitigating reliance on external factors. Within this category, the Demirjian staging method remains highly popular. However, certain studies have raised concerns about its potential for age overestimation(10,45,71,83,92), while the Willems method, modified from Demirjian's, has demonstrated greater accuracy in some studies(14,71,82,92,130) but yielded contrasting results in others.(13,15) The assessment of open apices, as pioneered by Cameriere, is also extensively employed and has been reported to provide more accurate age estimations compared to Demirjian(101) and Willems in some instances, although another has noted potential age underestimation.(72)

The second choice for age determination (23.1%), employed when all teeth have fully developed, involves assessing anatomic changes. RPV by Olze *et al.*(61) has proven valid for establishing a cutoff age at 21 years old. Moreover, pulp to tooth ratio is also popular in this aspect as many studies explored its potential in age estimation with promising results.(32,68,75,76,84,90) This approach remains adequate for age estimation but leaves room for some error due to independence from various factors, such as individual oral hygiene and socio-economic conditions. Some studies have sought to compare the accuracy of different methodological groups to determine the most precise approach for major-minor identification. Specifically, a specific cutoff value of I3M< 0.08, proposed by Cameriere, has demonstrated superior accuracy, sensitivity, and specificity compared to Demirjian's Stage H (completed mineralization), Stage D of mandibular third molar eruption (full eruption) by Olze *et al.* and Stage 1 of RPV (root canal not visually observed to apex).(85) However, for establishing a legal age of 21 years old, Stage 2 of RPV has been found to be more reliable in differentiating individuals over 21 years old, exhibiting fewer false positives compared to a score I3M < 0.02.(103) Lastly, AI has gained prominence, comprising 17.9% of the studies. Researchers have shown increasing interest in AI, with promising results indicating its potential to reduce human workload and minimize human errors, thus augmenting traditional processes.(23,108,110,117) Some studies have conducted comparisons between conventional AI-assisted models and traditional methods, with results indicating improved performance outcomes associated with AI.(23,108,110) Nevertheless, it is important to note that Kumagai *et al.* reported a slight advantage for the tradi-

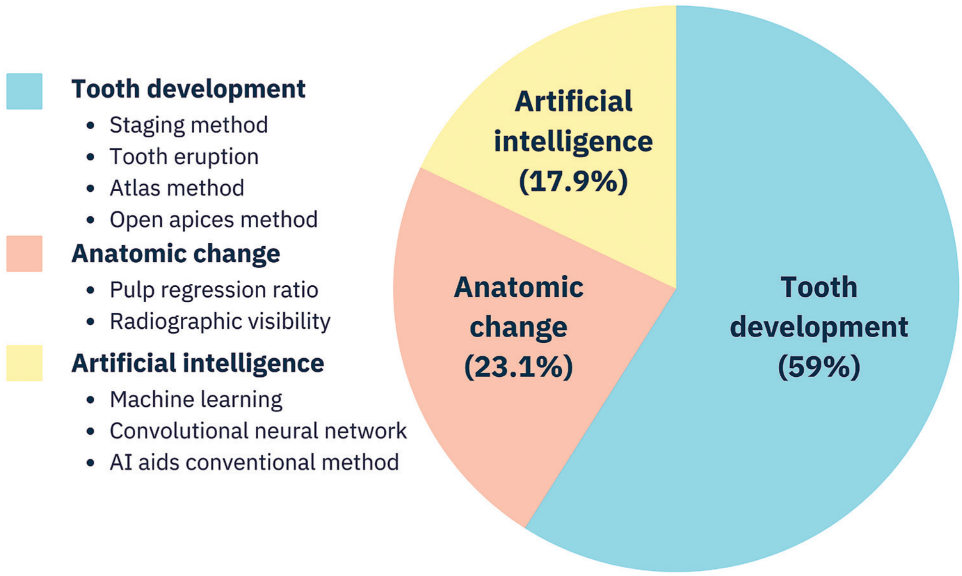

Figure 2: Percentage of age estimation methodologies in published articles included in this review.

tional (Demirjian) model over the AI model, although this was based on discussions with a relatively small number of participants.[121]

Conclusions

Age determination plays a pivotal role in forensics and legal contexts, and dental structures, renowned for their remarkable resilience, have emerged as an essential element in this pursuit. Dental radiography, notably OPG, stands as a non-invasive means to constantly contemplate age-related transformations in teeth. The radiological approach involves thoroughly examining diverse characteristics, facilitating the estimation of an individual's age, their grouping within specific age ranges, or determining whether they fall above or below designated thresholds. Age categorization opens through three distinctive phases: pre-natal, neo-natal, and post-natal; childhood and adolescence; and adulthood. While tooth development serves as generally used for age estimation in the initial phases, the observation of anatomical changes in adulthood takes priority. In recent times, there have been expanding explorations of AI as a robust tool in age estimation, yielding promising outcomes. AI holds the potential to enhance the precision of traditional methodologies, mitigating human errors and reducing associated workload, offering to produce ground for further development in coming years.

Table 1: Summary of findings in the articles assessing age estimation by tooth development methods. (see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
1	Albernaz Neves *et al.*, 2020[65]	I_{3M}	Portuguese	12-24	778	LL 8	OPG	Age ≥ 18: I_{3M}< 0.08: accuracy by AUC = 92.8, Se = 90.7%, Sp = 94.9%
2	Cameriere *et al.*, 2020[66]	I_{3M}	Albanian, Australian, Chinese, Colombian, Dominican, Egyptian, French, Italian, Indian, Japanese, Polonian, Chileans, Serbian, Turkish, South African	14-24	3228	LL 8	OPG	Age ≥ 18: I_{3M}< 0.08: The minimum Se = 47% (French), the maximum Se = 93% (Colombian), Sp >90% in all 15 countries
3	Gonçalves do Nascimento *et al.*, 2020[67]	Cameriere (Open apices)	Brazilian	5-14.99	429	LL 1-7	OPG	Mean difference (DA-CA): males = -0.32 years; females = -0.30 years; Total = -0.31 years R^2: males = 80.06%; females =78.95%; Total = 79.32%
5	Marrero-Ramos *et al.*, 2020[69]	Demirjian	Spanish	15-30	180	L 8	OPG	Age ≥ 18: Demirjian stage H in L8 OR: Observer1 = 29.333, Observer2 = 23.250
6	Memorando *et al.*, 2020[70]	Modified Demirjian	Filipino	9-23	384	LR 8	OPG	MAE: males = 1.05 years; females = 1.06 years, percentage error: males = 7.49; females = 7.43 Initial development of the third molars started around 9 years, and the root is completed around 19.
8	Paz Cortés *et al.*, 2020[71]	Willems, Demirjian, Nolla	Spanish	4-13	604	LL 1-7	OPG	Mean difference (DA-CA): Willems: males = -0.17 years; females = -0.35 years, Demirjian: males = -0.73 years; females = -0.68 years, Nolla: males = 0.82 years, females = 0.44 years
9	Rezende Machado *et al.*, 2020[72]	Cameriere (Open apices), Willems	Brazilian	6-14	180	LL 1-7	OPG	Estimated difference: Cameriere: males = 0.03 years; females = 0.05 years, Willems: males = -0.39 years; females = -0.47 years, Cameriere+Willems: males = -0.18 years; females = -0.21 years
10	Scendoni *et al.*, 2020[73]	I_{3M}	Russian	14-24	571	LL 8	OPG	Age < 18: I_{3M}> 0.08: males: PPV = 98.4%, NPV = 94.1 %, Se = 0.96, Sp = 0.98; females: PPV = 98.6%, NPV = 90.2%, Se = 0.93, Sp = 0.98
11	Sharma *et al.*, 2020[48]	Cameriere (Open apices), London Atlas	Indian	5-15.99	335	LL 1-7 (Cameriere), UR/LR (London Atlas)	OPG	Mean error value: Cameriere = 0.59 years (SD = 1.32), London Atlas = -0.03 years (SD = 0.69)

Table 1: Summary of findings in the articles assessing age estimation by tooth development methods. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
12	Sheriff *et al.*, 2020[74]	Willems, Bedek	Southern Indian	7-15	650	LL 1-7	OPG	MAE: Bedek's seven teeth: males = 0.85 years; females = 0.88 years; Total = 0.86 years, Willems: males = 1.02 years; females = 1.25 years, Total = 1.16 years
15	Yassin *et al.*, 2020[77]	Nolla	Southern Saudi Arabian	5-11	458	LL 1-7	OPG	Mean age error range: males = -2.68 to -6 months; females = -2.17 to -4.24 months
16	Alqerban *et al.*, 2021[78]	Willems, Saudi Arabian-specific model	Saudi Arabian	4-18	1146	LL 1-7	OPG	Overall, Willems MAE (1.37 years) is slightly higher than the Saudi Arabian-specific model MAE (1.33 years)
17	Franco *et al.*, 2021[79]	Gleiser and Hunt modified by Kohler	Russian	8-23	918	U/L 8	OPG	AUC: males = 0.915; females = 0.904
20	Pan *et al.*, 2021[82]	Demirjian, Willems, Chinese-specific Demirjian	Chinese	5-16	2367	LL 1-7	OPG	Accuracy (values within ± 1 year): Chinese-specific Demirjian: males = 83.7%; females = 79.6%, Demirjian: males = 73.9%; females = 70.2%, Willems: males = 75.0%; females = 75.9%
21	Pinchi *et al.*, 2021[83]	Demirjian, Willems	Italian	3.3-15.99	752	LL 1-7	OPG	Willem's method underestimated age, while Demirjian's overestimated for both healthy and juvenile rheumatoid arthritis-affected children.
23	Pyata *et al.*, 2021[85]	Demirjian, I_{3M}, Olze (third molars eruption and RPV)	Southern Indian	14-30	1070	L 8	OPG	Age ≥ 18: I3M< 0.08(most accurate): AUC: males = 0.95; females = 0.95, Se: males = 91.5%; females = 88.5%, Sp: males = 97.8%; females = 98.6%. Stage H of Demirjian: AUC: males = 0.94; females = 0.93, Se: males = 84.9%; females = 79.9%, Sp: males = 97.7%; females = 98.5%.
24	Rebouças *et al.*, 2021[86]	Demirjian	Brazilian	9-15.5	113	L 3, 7	OPG	The calcification of L7 was a significant predictor of skeletal maturity indicators (p = 0.003), whereas this correlation was not observed for L3 (p = 0.239).
25	Saranya *et al.*, 2021[87]	Demirjian	Southern Indian	12-20	640	LL 8	OPG	Age ≥ 16: probability obtained by Stage F of Demirjian, males = 93.9%; females = 96.6%
26	Shen *et al.*, 2021[23]	Machine learning: RF, SVM, L/R, Cameriere (Open apices)	Eastern Chinese	5-13.99	784	LL 1-7	OPG	MAE: SVM model = 0.489 years, traditional Cameriere = 0.846 years, Chinese Cameriere formula = 0.812 years

Table 1: Summary of findings in the articles assessing age estimation by tooth development methods. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
28	Thilak *et al.*, 2021[89]	I_{3M}	Indian	14-24	542	LL 8	OPG	Age ≥ 18: I3M = 0.08: accuracy by AUC, males = 0.95; females = 0.93, Se, males = 0.899; females = 0.854, Sp, males = 0.90; females = 0.93.
30	Zirk *et al.*, 2021[91]	Demirjian, Nolla	European	13-21	312	L 8	OPG, CBCT	Staging results for 2D and 3D imaging differed significantly. Demirjian: 21% showed a one-stage difference, agreement range = 47.4% (stage E) - 87% (stage G), Nolla: stages 3-6 had discrepancies in staging for more than two categorical variables. Inconsistencies were observed in stages 4-8.
31	Bedek *et al.*, 2022[92]	Demirjian, Willems, Haavikko	Croatian	4-18	1996	LL 1-7	OPG	Mean error value: Demirjian: males = 0.80 years; females = 0.84 years, Willems: males = 0.41 years; females = 0.22 years, Haavikko: males = -0.61 years; females = -0.82 years
32	Boedi *et al.*, 2022[93]	I_{3M}	Indonesian	8-23	222	U/L 8	OPG	Age ≥ 19: I3M ≤ 0.08 (males), 0.09 (females): accuracy = 80% for both sexes in the testing dataset.
33	Briem Stamm *et al.*, 2022[94]	Demirjian	Argentine	5-16	508	LL 1-7	OPG	Mean error value: Demirjian: males = 1.04 years; females = 1.15 years; for both sexes = 1.09 years
34	Caggiano *et al.*, 2022[95]	Demirjian	Southern Italian	3.3-15.99	460	U/L 8	OPG	Age>18: accuracy of Stage H of the Demirjian method for at least one third molar if the other third molars reached a stage equal or superior to F = 90.2%; when all third molars reached stage H = 97.4%.
36	Kuremoto *et al.*, 2022[97]	Development staging	Japanese	3-18	1024	FM	OPG	Cronbach's alpha coefficients: males = 0.987; females = 0.986. Females tended to form teeth faster than males until puberty, but males caught up with females after puberty.
38	Lin *et al.*, 2022[47]	London Atlas, Willems	Chinese Uyghur	10-16.99	831	UL/LL 1-7	OPG	MAE: London atlas = 0.86±0.75 years, Willems = 1.17±0.89 years, quick method = 0.70±0.54 years
39	Melo *et al.*, 2022[99]	Demirjian, I_{3M}	Spanish	10-26	1386	U/L 8	OPG	Age>18: Stage H of Demirjian method: accuracy = 93%, I_{3M} = 0.08: accuracy = 88%, for both males and females
41	Milani *et al.*, 2022[101]	Demirjian, Cameriere (Open apices)	Iranian	6-10	212	LL 1-7	OPG	Mean error value: Demirjian: males = 0.93 years; females = 0.84 years, Cameriere: males = 0.04 years; females = -0.06 years
43	Mónico *et al.*, 2022[45]	Demirjian	Portuguese, Spanish	6-14	574	LL 1-7	OPG	R^2: Demirjian global score = 0.651, tooth by tooth score = 0.717
44	Oh *et al.*, 2022[102]	Demirjian, Lee's method	Japanese, Korean	15-23	2657	U/L 7 8	OPG	R2: Koreans: males = 0.834; females = 0.855, Japanese: males = 0.682; females = 0.585

Table 1: Summary of findings in the articles assessing age estimation by tooth development methods. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
45	Parvathala *et al.*, 2022(103)	I_{3M}, Olze (RPV)	Southern Indian	16-30	910	L 8	OPG	Age ≥ 21: I_{3M}: cannot be used due to higher false positives. RPV stage 2: accuracy: males = 84.76%; female = 84.55%, Sp = 100% in both sexes
46	Prakoeswa *et al.*, 2022(104)	London Atlas, Willems	Indonesian	6-17	150	FM	OPG	Mean age difference: Willems = -0.41±0.90 years for males and females, Al Qahtani = 0.33±0.61 years for males and females.
50	Shan *et al.*, 2022(108)	Demirjian, Willem, Machine learning; SVR, BPNN, RF, AdaBoost, KNN, Light GBM, XGBoost, Extra trees, DT, GBDT, CatBoost	Southern Chinese	2-18	1477	FM	OPG	Chinese-specific Wilem is the most accurate in the traditional method (MAE: males = 0.76; female = 0.77) The GBDT, CatBoost, XGBoost, LightGBM, DT, Extra tree model reduced the error in dental age estimation compared to the traditional mathematical method (MAE: GBDT: males = 0.495; females = 0.441, CatBoost: males = 0.545; females = 0.594, LightGBM: males = 0.648; females = 0.642, DT: males = 0.602; female = 0.643, Extra tree: males =0.626; female = 0.682)
52	Shen *et al.*, 2022(110)	Demirjian, Machine learning; DT, BRR, KNN, Cameriere (Open apices)	Eastern Chinese	5-13	748	L 1-7	OPG	The highest accuracy is KNN model based on the Cameriere method. Demirjian: BRR: MAE = 0.510, R^2 = 0.928, KNN: MAE = 0.517, R^2 = 0.923, DT: MAE = 0.523, R^2 = 0.892, Traditional: MAE = 0.982 years Cameriere: KNN: MAE = 0.473, R2 = 0.940, BRR: MAE = 0.535, R^2 = 0.923, DT: MAE = 0.584, R^2 = 0.893, Traditional: MAE = 0.846 years
53	Wang *et al.*, 2022(111)	Willems	Eastern Chinese	11-16	1211	LL 1-7	OPG	MAE: Willems gender-specific method: males = 0.95 years; females = 1.00 years, Willems non-gender specific method: males = 1.02 years; females = 1.00 years
56	Abdul Rahim *et al.*, 2023(114)	Demirjian, Nolla, Moorrees	Malaysian, Chinese, Indian	6-15	200	UL/LL 1-7	OPG	Percentage agreement; Kappa values: Moorrees = 81%; 0.938, Nolla = 86 %; 0.922, Demirjian = 87%; 0.918
57	AlOtaibi *et al.*, 2023(115)	Demirjian, Moorrees, Fanning and Hunt, Gleiser and Hunt, Nolla, Chaillet, Nicodemo	Saudi Arabian	6-15.99	400	LL 1-7	OPG	Mean age difference: Demirjian = 0.15 years, Gleiser and Hunt = -1.00 years, Moorrees = -1.01 years, Fanning and Hunt = -1.01 years, Nolla = -1.29 years, Nicodemo = -1.72 years, Chaillet = -2.19 years

Table 1: Summary of findings in the articles assessing age estimation by tooth development methods. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
59	Bui *et al.*, 2023[117]	CNN; Mask R-CNN, U-Net with TDL or TDA-DL, I_{3M}	French, Ugandan	mean 17.9	456	L 8	OPG	The U-Net combined with TDL is the best approach for decision-making tools that replicated the I3M index for forensic experts with accuracy = 95% and MAE = 0.04±0.03 years.
60	El-Desouky *et al.*, 2023[118]	Cameriere (Open apices), Egyptian specific Cameriere	Egyptian	5-18	762	L 1-7	OPG	Mean age difference: Egyptian-specific Cameriere: males = -0.12 years; females = 0.1 years, Cameriere: males = -0.59 years; females = -0.53 years
62	Kuhnen *et al.*, 2023[120]	Moorrees	Brazilian	2-25	1100	UL/LL 1-8	OPG	The numerical tables of the chronology of dental mineralization stages for Brazilian individuals were delivered using modified Moorrees *et al.* Only upper and lower canines differed between sexes.
63	Kumagai *et al.*, 2023(121)	Demirjian, Machine learning: KNN, SVM, L/R, DT, RF, XGBoost, MLP	Korean, Japanese	15-23	2657	U/L 7 8	OPG	The accuracy of the conventional method was slightly higher than machine learning models, with MAE < 0.21 years, RMSE < 0.24 years. The highest different MAE and RMSE in the internal test set in the female group (MAE: KNN = 1.06, Conventional method = 0.85, RMSE: KNN = 1.32, Conventional method = 1.08)
64	Kwon *et al.*, 2023[122]	Demirjian, Willem	Chinese	8-14.99	1259	L 1-7	OPG	Mean age difference in 2009-2011: Demirjian: males = 0.65±0.97 years; females = 0.48±1.04 years, Willems: males = 0.19 ± 1.00 years; females = -0.08±0.98 years Mean age difference in 2021: Demirjian: males = -0.51±0.73 years; females = -0.48±0.80 years, Willems: males = -0.80±0.71 years; females = -0.82±0.87 years Environmental factors and dietary habits affect dental development.
65	Lopatin *et al.*, 2023[123]	Primary tooth development	Polish	3mo-14	58	Primary teeth	OPG	Tooth maturity stage 8 is reached earlier in males than females for all deciduous teeth except molars. Both sexes lose deciduous teeth after pre-puberty, with males losing at 3-9 years and females at 2-7 years.

Table 1: Summary of findings in the articles assessing age estimation by tooth development methods. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
68	Timme *et al.*, 2023[126]	Olze (third molars eruption), Willmot, New model	German	15-25	211	L 8	OPG	Degree of correlation with Spearman's coefficients: Olze, new method: males= 0.58; females = 0.45
69	Topal *et al.*, 2023[127]	Willems	Turkish	9-15	80	LL 1-97	OPG	Children with multiple persistent primary teeth can experience delayed dental development by 0.5-4 years. Willems method can assess their dental development.

Abbreviations: AUC (area under curve), BPNN (backpropagation neural network), BRR (Bayesian ridge regression), CA (chronological age), CBCT (cone-beam computed tomography), CNN (convolutional neural network), DA (dental age), DT (decision tree), FM (full mouth), GBDT (gradient boosting decision tree), GBM (gradient boosting machine), I3M (third molar maturity index, KNN (K-nearest neighbor), L (lower teeth), LL (lower left teeth), L/R (linear regression), LR (lower right teeth), MAE (mean absolute error), MLP (multilayer perceptron), NPV (negative predictive values), OPG (orthopantomography), OR (odd ratios), PPV (positive predictive values), RF (random forest), RMSE (root mean square error), RPV (root pulp visibility), SD (standard deviation), Se (sensitivity), Sp (specificity), SVM (support vector machine), SVR (support vector regression), TDA (topological data analysis), TDA-DL (topological data analysis with deep learning), U/L (upper and lower teeth, UR (upper right teeth), XGBoost (extreme gradient boosting)

Table 2: Summary of findings in the articles assessing age estimation by anatomic change method. (see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
4	Helmy *et al.*, 2020[68]	pulp/tooth volume ratio	Egyptian	21-50	505	U/L 7	CBCT	MAE: Upper teeth = 4.89 years, Lower teeth = 4.61 years
7	Miranda *et al.*, 2020[32]	Kvaal, Cameriere (pulp/tooth ratio)	Brazilian	20-59	1280	U/L 3	Periapical	Kvaal was more accurate for the age groups of 20-29 (UR3: ME = 4.63) and 30-39 years (LL3: ME= 5.42), while Cameriere performed better for individuals over 40 years of age (UL3: ME = 6.08)
13	Timme *et al.*, 2020[75]	pulp/tooth volume ratio	German	48-78	4	UR 1, 4 UL 3, 6	MRI	UTE-MRI at 9.4 T is a radiation-free procedure that allows for the determination of dental pulp volume at high spatial resolution, making it a valuable tool for forensic age assessment of living persons.
14	Yang *et al.*, 2020[76]	pulp/tooth volume ratio	Eastern Chinese	8.18-19.92	230	UL 1, 3	CBCT	UL1: R2 = 0.44, SEE = 2.58, UL3: R2 = 0.69, SEE = 1.91
19	Manthapuri *et al.*, 2021[81]	Olze (RPV)	Indian	12-20	760	L 6	OPG	Age>16: RPV stage 2: Se: males = 0.6; females = 0.65, Sp: males = 0.96; females = 0.97, accuracy: males = 0.77; females = 0.8, false negatives = 34.5% (both sexes)
22	Pires *et al.*, 2021[84]	Kvaal	Portuguese	>=21	158	U/L Ant	CBCT	Mean error in age: coronal section = -21.4 years, sagittal section = -26.3 years
23	Pyata *et al.*, 2021[85]	Demirjian, I_{3M}, Olze (third molars eruption and RPV)	Southern Indian	14-30	1070	L 8	OPG	Age ≥ 18: RPV stage 1 or higher and stage D of third molars eruption were not recommended due to the higher incidence of incomplete mineralization in younger age groups and impaction.
27	Tantanapornkul *et al.*, 2021[88]	Olze (PLV)	Thai	16-26	800	L 8	OPG	Periodontal ligament visibility stage 2 can be confirmed that the individual is at least 18 years of age according to the distribution table
29	Timme *et al.*, 2021[90]	Pulp volume	German	18-78	13	FM	MRI, CBCT	UTE-MRI and CBCT are reliable methods for age estimation using pulp volume. MRI has a smaller variation in results but displays smaller pulp volume. Method-specific reference values are needed for practical age assessment with CBCT or MRI.
35	Gunacar *et al.*, 2022[96]	Olze (RPV)	Turkish	16-68	290	L 8	OPG, CBCT	The presence of RPV Stage 3 can be used to identify individuals over 18. The use of CBCT for RPV evaluation is recommended for available cases.

Table 2: Summary of findings in the articles assessing age estimation by anatomic change method. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
40	Merdietio Boedi *et al.*, 2022[100]	Regression change of crown and root	Indonesian	20-60	192	U Ant	CBCT	MAE: U2 = 5.3 years ($R^2 = 0.67$), U3 = 5.45 years ($R^2 = 0.66$), U1 = 6.19 years ($R^2 = 0.59$)
45	Parvathala *et al.*, 2022[103]	I_{3M}, Olze (RPV)	Southern Indian	16-30	910	L 8	OPG	Age ≥ 21: I_{3M}: cannot be used due to higher false positives. RPV stage 2: accuracy: males = 84.76%; female = 84.55%, Sp = 100% in both sexes
47	Santos *et al.*, 2022[105]	Pulp volume, Multiple regression	Spanish	18-85	373	U 1	CBCT	SEE: axial linear measurements = ±10.9 years ($R^2 = 0.49$), axial ratios = ±10.8 years ($R^2 = 0.50$), multiplanar linear measurements = ±10.9 years ($R^2 = 0.52$), multiplanar ratios = ±10.7 years ($R^2 = 0.51$)
49	Shah *et al.*, 2022[107]	TCI, Drusini	Western Indian	21-60	300	U/L 3, L 4-7	OPG	MAE <10 years for all the teeth, with no statistically significant difference between the mean chronological age and mean calculated age for both pulp/tooth area ratios of U/L3 and TCI of L 4-7 (p-value > 0.05).
58	Bjørk *et al.*, 2023[116]	Tooth/tissue volume, Linear regression	Bayesian	14-24	67	U/L 8	MRI	MRI segmentation of tooth tissue volumes can be useful in predicting the age of sub-adults older than 18 years (p-value = 3.4×10^{-9}).
66	Merdietio Boedi *et al.*, 2023[124]	Crown segment secondary dentine deposit regression	Indonesian	20-60	99	U Ant	CBCT	The highest R2 (0.6) was obtained from the U3, indicating a good model performance in anterior maxillary teeth. The enamel-to-dentine volume ratio and pulp-to-dentine volume ratio are related to chronological age.
67	Sharma *et al.*, 2023[125]	TCI	Indian	20-70	700	L 4	OPG	Mean age difference: males = 1.48±3.82 (SE = 0.76); females = 0.13±17.65(SE = 3.53)
70	Vangala *et al.*, 2023[128]	Olze (RPV)	Southern Indian	15-30	930	L 6-8	OPG	RPV stage 3 in L6 were at least older than 21 years. RPV stage 2 and 3 in L7 were at least older than 21 years. RPV stage 1-3 in L8 were at least older than 21 years. Using these methods with other age estimation methods is recommended due to the higher percentage of false negatives with L 6-7.

Abbreviations: AUC (area under curve), Ant (anterior teeth), CBCT (cone-beam computed tomography), FM (full mouth), I3M (third molar maturity index), L (lower teeth), MAE (mean absolute error), ME (mean error), MRI (magnetic resonance imaging), OPG (orthopantomogram), PLV (periodontal ligament visibility), RPV (root pulp visibility), Se (sensitivity), SE (standard error), SEE (standard error of the estimate), Sp (specificity), TCI (tooth-coronal index), U/L (upper and Lower teeth), U (upper teeth), UTE-MRI (ultrashort echo time magnetic resonance imaging)

Table 3: Summary of findings in the articles assessing age estimation by artificial intelligence method. (see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
18	Kim *et al.*, 2021[80]	CNN; ResNet152, Tooth-wise age group prediction	Korean	0->60	1586	U/L 6	OPG	Accuracy range = 89.05-90.27%, AUC range = 0.94-0.98 for all age groups The CNNs focused on tooth pulp, alveolar bone level, or interdental space, depending on the age and location of the tooth.
26	Shen *et al.*, 2021[23]	Machine learning; RF, SVM, L/R, Cameriere (Open apices)	Eastern Chinese	5-13.99	748	LL 1-7	OPG	MAE: SVM model = 0.489 years, traditional Cameriere = 0.846 years, Chinese Cameriere formula = 0.812 years
37	Lee *et al.*, 2022[98]	Machine learning;LDA, L/R, MLP, SVM, XGBoost),18 selected features	Korean	11-69	471	FM	OPG	Mean AUC range: 10-19 years group = 0.85-0.87, 60-69 years group = 0.80-0.90, which are the best scores. The L-Pulp Area was important for discriminating 10-49 years group, and L-Crown, U-Crown, L-Implant, U-Implant, and Periodontitis were for 50-69 years group.
42	Milošević *et al.*, 2022[6]	CNN; Dense Net201, InceptionResNetV2, ResNet50, VGG16, VGG19, Xception	Croatian	19-90	4035	FM	OPG	Whole OPG: MAE = 3.96 years, MEE = 2.95 years Individual teeth: L8 best score: MAE = 6.39 years, MEE = 4.68 years Dental variations, diseases, and missing teeth do not pose a problem to the proposed model.
48	Santosh *et al.*, 2022[106]	Machine learning; MSVM, LIBSVM	Indian	1->60	1142	FM	OPG	MSVM and LIBSVM models: accuracy = 96% in age estimation and gender prediction.
50	Shan *et al.*, 2022[108]	Demirjian, Willem, Machine learning; SVR, BPNN, RF, AdaBoost, KNN, Light GBM, XGBoost, Extra trees, DT, GBDT, CatBoost	Southern Chinese	2-18	1477	FM	OPG	Chinese-specific Wilem is the most accurate in the traditional method (MAE: males = 0.76; female = 0.77) The GBDT, CatBoost, XGBoost, LightGBM, DT, Extra tree model reduced the error in dental age estimation compared to the traditional mathematical method (MAE: GBDT: males = 0.495; females = 0.441, CatBoost: males = 0.545; females = 0.594, LightGBM: males = 0.648; females = 0.642, DT: males = 0.602; female = 0.643, Extra tree: males =0.626; female = 0.682)

Table 3: Summary of findings in the articles assessing age estimation by artificial intelligence method. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
51	Sharifonnasabi *et al.*, 2022[109]	HCNN- KNN, CNN, ResNet, GoogLeNet Inception	Malaysian	1-17	1922	FM	OPG	HCNN-KNN: accuracy: age range of 1 year = 99.98%, 6 months = 99.96%, 3 months = 99.87%, 1 month = 98.78%
52	Shen *et al.*, 2022[110]	Demirjian, Machine learning; DT, BRR, KNN, Cameriere (Open apices)	Eastern Chinese	5-13	748	L 1-7	OPG	The highest accuracy is KNN model based on the Cameriere method. Demirjian: BRR: MAE = 0.510, R^2 = 0.928, KNN: MAE = 0.517, R^2 = 0.923, DT: MAE = 0.523, R^2 = 0.892, Traditional: MAE = 0.982 years Cameriere: KNN: MAE = 0.473, R^2 = 0.940, BRR: MAE = 0.535, R^2 = 0.923, DT: MAE = 0.584, R^2 = 0.893, Traditional: MAE = 0.846 years
54	Wang *et al.*, 2022[112]	CNN: DENSEN (Based on SSR-Net), Bayesian CNNs Net, DANet	Chinese	3-85	1903	FM	OPG	MAE: DENSEN: 3-11 years group = 0.6885 years, 12-18 years group = 0.7615 years, 19-25 years group = 1.3502 years, and >25 years group = 2.8770 years
55	Zaborowicz *et al.*, 2022[113]	POD-GP, Tooth Geometry Indicators	Polish	4-18	619	U/L 3 5-7	OPG	Accuracy = 95%, MAE = ±7.5 months
59	Bui *et al.*, 2023[117]	CNN; Mask R-CNN, U-Net with and without TDA-DL), I3M	French, Ugandan	Mean 17.9	456	L 8	OPG	The U-Net combined with TDL is the best approach for decision-making tools that replicated the I3M index for forensic experts with accuracy = 95% and MAE = 0.04 ± 0.03 years.
61	Kim *et al.*, 2023[119]	CNN	Korean	10s-70s	10023	FM	OPG	Accuracy = 53.846%, with a tolerance of ±5 years
63	Kumagai *et al.*, 2023[121]	Demirjian, Machine learning: KNN, SVM, L/R, DT, RF, XGBoost, MLP	Korean, Japanese	15-23	2657	U/L 7 8	OPG	The accuracy of the conventional method was slightly higher than machine learning models, with MAE < 0.21 years, RMSE < 0.24 years. The highest different MAE and RMSE in the internal test set in the female group (MAE: KNN = 1.06, Conventional method = 0.85, RMSE: KNN = 1.32, Conventional method = 1.08)

Table 3: Summary of findings in the articles assessing age estimation by artificial intelligence method. (continued; see abbreviations in the footnote)

No.	Author (Year)	Method	Population	Age range (years)	Number of samples	Region of interest	Radiographic modality	Findings
71	Wang *et al.*, 2023[129]	CNN; VGG16, ResNet101	Chinese	6-20	9586	LL 1-7	OPG	Accuracy: VGG16 model = 93.63%, ResNet101 = 88.73% in the 6-to-8-year-old group.

Abbreviations: AdaBoost (adaptive boosting), AUC (area under curve), BPNN (backpropagation neural network), BRR (Bayesian ridge regression), CNN (convolutional neural network), DT (decision tree), FM (full mouth), GBM (gradient boosting machine), GBDT (gradient boosting decision tree), HCNN-KNN (Hybrid HCNN-KNN), I3M (third molar maturity index), KNN (K-nearest neighbor), LDA (linear discriminant analysis), L (lower teeth), LL (lower left teeth), L/R (linear regression), LIBSVM (library for support vector machines), MAE (mean absolute error), MEE (median estimate error), MLP (multilayer perceptron), MSVM (multiclass support vector machine, OPG (orthopantomography), POD-GP (proper orthogonal decomposition and gaussian processes), RF (random forest), RMSE (root mean square error), SVM (support vector machine), SVR (support vector regression), TDA (topological data analysis), TDA-DL (topological data analysis with deep learning), U/L (upper and lower teeth), XGBoost (extreme gradient boosting)

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