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Review Article

Forensic Section

AI-Powered Dental Forensics in Transforming Age Estimation Techniques: A Narrative Review

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ABSTRACT

Artificial Intelligence (AI) has opened new avenues for researchers all over the world with its rapid results, accuracy and efficiency. This paper specifically aims to identify the role of AI in forensic odontology by assisting odontologists in age estimation. It discusses the evolution from conventional methods to fast and efficient AI models, including Convolutional Neural Networks (CNN), Deep Learning (DL) and Machine Learning (ML) and compares the efficiency of each to conclude which AI model yields the best results for researchers. The paper also highlights the role of the CNN network in dental age estimation using Orthopantomogram (OPG), Cone Beam Computed Tomography (CBCT) and Magnetic Resonance Imaging (MRI) datasets. It aims to help researchers incorporate global advancements into their studies, with a focus on applications for the Indian population. OPG is widely used in routine dental examinations due to its efficiency and accessibility; however, it has limitations, such as image distortion and the lack of 3D visualisation. AI models, particularly CNNs, have improved the accuracy of age estimation from OPG images. Magnetic Resonance Imaging (MRI), though less commonly utilised, is beneficial for non invasive and precise age estimation in younger individuals because it provides clear images of pulp cavities. Cone Beam Computed Tomography (CBCT) offers superior 3D imaging, allowing for more accurate assessments of pulp-to-tooth ratios and root development, although it involves higher radiation exposure. This review highlights how combining AI with different imaging techniques can enhance accuracy, reduce human error and address population-specific variations in forensic age estimation.

Keywords: Artificial intellegence, Convolutional neural networks, Dental age estimation, Machine learning

INTRODUCTION

Age is defined as the length of time a living being or individual has lived after birth [1]. Being an indicator of health, growth and development, age is of great interest to physicians, dentists, anthropologists and forensic experts [2]. Age estimation, a subdivision of forensic sciences, is of enormous importance in forensic medicine for the personal identification of the deceased, as well as in cases of juvenile crimes, sexual assaults, domestic disputes and accidents, where there might be deliberate falsification of age [1,3].

The chronological age of an individual is derived from the date of birth, which is typically confirmed by birth registration documents. However, birth registration is still not rigorously followed across the globe. In cases where the date of birth is uncertain, biological age is considered a marker of maturity to estimate age, including skeletal age, morphological age, secondary sex characteristics and dental age [2]. As dental age estimation is less variable and less affected by environmental factors, it has gained greater acceptance compared to other indices [4]. Teeth are unique in structure and follow a sequential developmental pattern. Furthermore, teeth are the most durable components of the body because of their resilience to most environmental stresses [5]. The various methods of dental age estimation include morphological, biochemical and radiological approaches.

Age-related changes in teeth can be divided into three categories: formative, degenerative and histological. Until adulthood, formative or developmental changes are good predictors of age and include tooth eruption and calcification. Degenerative changes, such as attrition, periodontal diseases, secondary dentin deposition, root translucency, cementum apposition and root resorption, become substantial with increasing age. However, quantitative evaluation of these changes typically necessitates the extraction and sectioning of teeth, which is impractical and unethical in living individuals [1].

Radiological assessment of age is a simple, non invasive and reproducible method that can be applied to both living individuals and the unidentified deceased [6]. It employs various types of radiographs and imaging techniques to assess features such as the appearance of tooth germs, mineralisation, degree of growth completion, eruption status, degree of root completion, measurement of open apices, tooth-to-pulp ratio, formation of secondary dentin and third molar development, among others [7].

In children, age estimation techniques based on dental maturation can be divided into those using the atlas approach and those employing scoring systems, such as the methods developed by Moorrees Anderson, Schour and Massler and Demirjian. Age estimation methods in adults include morphological and radiological techniques, such as those proposed by Bang and Ramn, Solheim, Gustafson, Kvaal and others [1]. Despite the numerous methods of age determination that have been proposed, a universal system has yet to be achieved, as different ethnic population groups exhibit varying characteristics [1].

AI is a branch of computer science that focuses on creating machines or systems capable of performing tasks that would typically require human intelligence. The different categories within AI include ML, natural language processing, robotics, computer vision and expert systems [8]. The DL, a subfield of AI, is inspired by the structure of the human brain and uses neural networks to acquire knowledge from large datasets [9]. ML, another subfield of AI, focuses on developing algorithms and statistical models that enable computers to learn from data without explicit programming [9]. Traditional methods and statistical analyses are regularly used in forensic age estimation; however, errors due to various factors may impede the desired accuracy. With the advancement of ML, AI has emerged as a promising tool in forensic age estimation. AI in this context enables rapid results with improved accuracy compared to the time-consuming and costly conventional methods, making the application of AI in this field increasingly attractive [10]. To further develop AI applications, it is vital to diversify datasets through continuous updates on algorithms and the collection of varied data for different ethnicities, genders and age groups. This would help eliminate biases within the AI system and adopt a more integrated approach [10].

This paper explores the role of AI in age estimation, tracing the evolution from conventional methods to advanced AI models such as CNN, DL and ML, comparing their efficiencies to identify the most effective approach. The review highlights the application of CNN in dental age estimation using datasets from OPG, CBCT and MRI. Additionally, it aims to guide researchers in integrating global advancements into ongoing studies, with a specific focus on applications for the Indian population.

METHODOLOGY

The literature review was conducted through a comprehensive analysis of research published between 2015 and 2024. It includes studies employing both conventional and AI-based models in the field of dental age estimation. A rigorous search was performed across multiple online databases, including PubMed, Scopus, Web of Science, ScienceDirect, ResearchGate, IEEE Xplore and Elsevier. A total of 50 peer-reviewed articles were identified, reviewed and critically analysed to synthesise the findings and evaluate the advancements in this domain.

DISCUSSION

AI and Dental Age Estimation

Analysis of conventional methods for dental age estimation: Dental age estimation methods have evolved significantly, each with its strengths and limitations. The Demirjian method, William's approach, the modified Demirjian method, the Gustafson method and the Cameriere open apices method are among the most widely accepted dental age estimation techniques worldwide. These methods have been applied to different populations and various datasets using regression models, which are specific population-based formulas, for many years.

The Demirjian Method, widely used for its simplicity in assessing mandibular teeth, has highlighted the need for regional calibrations due to biases in age estimation. William's Method, incorporating population-specific adjustments, offers improved accuracy and consistency across age groups, thereby enhancing its forensic applicability. Cameriere's Open Apices Method and the I3M Technique demonstrate high accuracy and reliability, particularly for juvenile and adult classifications. These methods utilise panoramic radiographs and advanced regression models, showcasing strong correlations with chronological age. Traditional approaches such as Gustafson's and Kedici's Methods, while foundational, face challenges with subjectivity and higher error rates, prompting a shift towards quantitative and AI-driven techniques [11].

Recent regional adaptations in India, incorporating population-specific formulas, emphasise the necessity of demographic calibrations to improve accuracy. These advancements underscore the vital role of customisation and the integration of advanced technologies in enhancing forensic age estimation.

AI Models Evolution

From 2020 onwards, advancements in dental age estimation have increasingly focused on leveraging diverse radiographic techniques such as OPG, CBCT and MRI, combined with emerging technologies like AI. These developments have significantly enhanced the precision and reliability of dental age estimation by enabling detailed analysis of dental structures and developmental markers. This section presents a comprehensive discussion of studies conducted from 2020 to the present, focusing on various imaging techniques and their results.

To facilitate a clearer and more efficient understanding, the data has been organised into concise tables. These tables highlight the imaging techniques utilised, the AI tools employed and the corresponding results, along with essential details such as the age groups considered, sample sizes and the populations studied. This structured format provides a succinct overview, offering valuable insights at a glance. The aim is to assist scholars and researchers in identifying the most suitable imaging techniques and AI tools for their specific research needs or experimental designs. By summarising the findings in this manner ([Table/Fig-1]: OPG; [Table/Fig-2]: MRI; [Table/Fig-3]: CBCT), the tables/figures serve as practical resources for guiding future studies and improving the efficiency of forensic age estimation methodologies [12-29].

Author and year of publication	AI model	Country	Sample size	Age (years)	Results	Conclusion
Kahaki SMM et al., (2019) [12]	DCNN model	Malaysia	456 patients	1-17	Male patient age was predicted better than female patient using DCNN model	DCNN model showed efficient classification and high performance.
Vila-Blanco N et al., (2020) [13]	Deep Learning (DL) (DANet DASnet)	Spanish	2289 images	5-45	DASnet – the AUC value went ahead of 0.92. Sex based age estimation was not biased	- DASnet gave better results. Posterior teeth of the inferior arch usually contribute more to age prediction.
Chaudhry K et al., (2020) [14]	ML (Support Vector Machine (SVM) Random Forest (RF) Logistic Regression (LR)) DL (A 2 layer network)	Group 1- (Southeast) Dravidian ethnicity. Andhra Pradesh, Telangana. Group 2- (Northwest) Aryan Ethnicity, India.	1000 images	5-14	2-Class: SVM: 86.8% DL: 87.2% 3-Class SVM: 66% RF: 60% 5-Class: SVM: 42.8% RF: 47.6%	DL outperformed ML, but performance dropped with more classification categories (e.g., 5-class).
Shen S et al., (2021) [15]	ML model assisted with Cameriere method. RF, SVM	Eastern China	748 images	10-20	SVM: MAE- 0.489 years. RF : MAE- 0.495 years	SVM: worked best for overall accuracy. RF gave high performance to predict coefficient
Milošević D et al., (2021) [16]	CNN network (DenseNet201 InceptionResNetV 2 ResNet50 VGG16 VGG19 Xception	Croatia	4035 images	19-30	OPG : MAE- 2.95 years. Individual tooth model: MAE- 6.30-8 year	Models performance on individual teeth was weaker. VGG16 outperformance all models
Mualla N, et al., (2019) [17]	CNN model: AlexNet and ResNet-101	Kuwait	1429	0-70	(K-NN) was found best in the classifier	AlexNet and ResNet gave a high-performance
Kim S et al., (2021) [18]	DNN with 152 layers (ResNet152)	Kyung Hee University (IRB) dataset, Seoul, Korea	2025	0-60	The overall accuracy when using a CNN model is 90.37±0.93%	The accuracy of estimation was 89.05 to 90.27%

Guo YC et al., (2021) [19]	CNN model (Efficient Net and SE- ResNet)	Chinese	10,257	5–24	Threshold of 14 and 16 years reaches over 95% and that of 18 years old reaches 93.3%	CNN models are better with high accuracy.
Wang X et al., 2022 [20]	-DL ; (DENSEN – SSR-Net) -Bayesian CNNs Net DANet	Shaanxi, China	1903 images	>25 years	DENSEN's MAE; Children - 0.6885 years. Adults - 2.8770 years	DENSEN outperformed Bayesian CNNs Net and DANet in accuracy.
Wu T-J et al., (2022) [21]	ML: Gaussian Process Regression (GPR), CNN; EfficientNet-B0	Taiwan	2,431 images	3-18	Both models showed MAE below 0.05 years	Both ML and CNN models showed high accuracy.
Lee T et al., (2024) [22]	Feature cluster- based age-estimation (FCA) model, backbone models include ResNet50, VGG16 and MobileNetV2	South Korea	9,663 images	5-30	FCA model; MAE- 2.85 years	-FCA model outperforms conventional single- regressor models. -Improved performance in challenging age groups (children and elderly).
Matthijs L et al., (2024) [23]	CNN trained for optimal staging accuracy	Belgium	1639 radiographs	Not specified	Accuracy: 0.53, Mean Absolute Difference: 0.71, Cohen's Kappa: 0.71, ICC: 0.89	Automated mandibular molar staging is promising, but including incisors may reduce accuracy.

[Table/Fig-1]: Dental age estimation using OPG and AI.
DAE-OPG-AI: Dental age estimation using orthopantomogram and AI; OPG: Orthopantomogram; AI: Artificial intelligence; CNN: Convolutional neural network; DCNN: Deep convolutional neural network; DANet: Deep attention network, DASNet: Deep attention-based segmentation network: SVM: Support vector machine; RF: Random forest; LR: Logistic regression; MAE: Mean absolute error; AUC: Area under curve; GRAD-CAM: Gradient-weighted class activation mapping; SE-ResNet: Squeeze-and-excitation residual network; GMM: Gaussian mixture model; SGD: Stochastic gradient descent.

Research based on OPG has highlighted the critical role of AI-driven methods in improving the precision of dental age estimation. The automation of age prediction using OPG has been significantly enhanced by DL models, such as CNN, with various models emerging as particularly effective due to their superior accuracy, as shown in [Table/Fig-1] by the authors. OPG is essential for assessing tooth growth, including molar eruption and root formation, making it a key tool for age estimation. However, image distortion and the lack of 3D details limit its accuracy compared to other advanced imaging techniques [18]. Despite these drawbacks, OPG remains widely used due to its ease of application and cost-effectiveness.

MRI, though not a common choice for dental age estimation, is particularly useful for visualising tooth pulp cavities. Its ability to capture soft-tissue details makes it valuable for assessing tooth development in younger individuals [24]. While MRI shows significant potential for enhancing forensic age estimation, especially in cases involving children or limited dental records, its adoption is hindered by higher costs and longer scan times. To date, relatively few studies have been conducted to verify the accuracy and efficiency of using AI and MRI for dental age estimation [Table/Fig-2].

CBCT has emerged as a powerful tool for age estimation, offering 3D imaging capabilities that enable a comprehensive evaluation of dental anatomy. By assessing pulp-to-tooth ratios and root development, CBCT provides highly accurate results, outperforming traditional 2D X-rays. Despite concerns over higher radiation exposure, advancements in low-dose protocols and its diagnostic precision make CBCT increasingly valuable in forensic and clinical applications.

Studies have demonstrated that CBCT yields more precise results than conventional 2D X-rays, especially when determining pulp-to-tooth ratios and evaluating the growth of tooth roots. Research has shown that CBCT may accurately determine age, particularly when it focuses on areas such as the mandibular angle and utilises small Fields of View (FOV). Although CBCT requires greater radiation doses than conventional X-rays, improvements in low-dose procedures and its superior diagnostic potential support its expanding use in forensic and clinical contexts [Table/Fig-3].

Author and Year of publication	AI model	Population	Sample size	Age (years)	Results	Conclusion
Stern D et al., (2019) [24]	Deep Convolutional Neural Network (DCNN); -early fusion, middle fusion, late fusion.	Caucasian	322	13-25	Best Model (Late Fusion DCNN); MAE - 1.01±0.74 years. AUC- 0.98	Regression-based model performed better than other binary classification model. Multifactorial age estimation is achievable by fusing age-relevant information from multiple data sources using DCNN architectures.

[Table/Fig-2]: Dental age estimation using MRI and AI.
DAE-MRI-AI: Dental age estimation using magnetic resonance imaging - artificial intelligence; MRI: Magnetic resonance imaging; DCNN: Deep convolutional neural network; MAE: Mean absolute error; AUC: Area under curve; CNN: Convolutional neural network

Author and year of publication	AI model	Population	Sample size	Age (years)	Results	Conclusion
Zheng Q et al., (2020) [25]	CNN (Resblock)	Chinese	180	15-25	The correlation coefficient was 0.74	Model provides accurate, rapid and automatic segmentation of pulp chamber.
Saric R et al., (2022) [26]	Support Vector Machines, Random forest.	Bosnians and Herzegovini-ans	150	20-60	Correlation coefficient of 0.803 and MAE of 6.022	Random forest classifier produced greater results.
Song Y et al., (2023) [27]	U-NET CNN	Chinese	20 sets of images	15-60	Established model; MAE- 6.72 years	U-Net model accurately segments the intact pulp cavity.
Dogan OB et al., (2023) [28]	Machine Learning (ML) model- Support vector machine (SVM), Classification, RF.	Turkish	236	18-70	Classification performances of the models were generally low	Algorithms demonstrated the highest accuracy in the (18-25 years) age group compared to other age ranges.
Krishnapriya BDSJ et al., (2023) [29]	Imaging technology Segmentation software; ITK SNAP version 3.8.0	Odisha, Indians	120	20-25	Strong negative correlation between age and PV/TV ratio	CBCT-based PV/TV was the robust method for age classification.

[Table/Fig-3]: Dental age estimation using CBCT and AI.
SVM: Support vector machine; RF: Random forest; MAE: Mean absolute error; U-Net: U-shaped convolutional neural network; ITK-SNAP: Insight toolkit - segmentation and processing, PV/TV Ratio: Pulp volume to total volume ratio; ICCs: Intraclass correlation coefficients

CONCLUSION(S)

The future of dental age estimation lies in integrating AI with multimodal imaging. The DL models have shown potential in automating the process, reducing human error and improving speed. Further research is needed to address population-specific variations and optimise the use of multiple imaging techniques. Exploring the combination of AI with different imaging methods in India could enhance age estimation accuracy and reliability across diverse populations.

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