World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

Integrating artificial intelligence and adult dental age estimation in forensic identification: A literature review

Arofi Kurniawan [1,*], Aisyah Novianti [2], Feby Ayu Lestari [2] and Sheryn Marcha Ramaniasari [2]

[1] *Department of Forensic Odontology, Faculty of Dental Medicine, Universitas Airlangga, Surabaya, Indonesia*

[2] *Magister of Dental Health Sciences, Faculty of Dental Medicine, Universitas Airlangga, Surabaya, Indonesia.*

World Journal of Advanced Research and Reviews, 2024, 21(02), 1374–1379

Publication history: Received on 13 January 2024; revised on 20 February 2024; accepted on 22 February 2024

Article DOI: https://doi.org/10.30574/wjarr.2024.21.2.0605

Abstract

Age estimation is crucial in various forensic fields, including forensic medicine, anthropology, and demographic studies. Adult dental age estimation is affected by multiple factors, resulting in discrepancies between dental age and chronological age. The development of artificial intelligence (AI) technology has led to extensive investigations in forensic sciences, encompassing several areas such as facial recognition, age, sex identification, and DNA analysis. Adult age estimation methods commonly used include the pulp-tooth ratio approach, the Harris & Nortje method, and the Van Heerden method. AI approaches such as Fuzzy Logic (FL), Evolutionary Computing (EC), and Machine Learning (ML) are being extensively applied. These techniques use algorithms to imitate human thinking and behavior. Deep learning techniques, explicitly using deep convolutional neural networks (DCNN), enable age estimation by segmenting images and making measurements, replicating the cognitive processes of radiologists when computing indices such as the third molar maturity (I3M) index. Also, DCNNs automatically optimize teeth segmentation in dental X-ray images, improving image refining and analysis efficiency. AI integration in forensic dentistry improves the precision and effectiveness of dental data processing while significantly accelerating individual identification procedures. Incorporating this technology shows potential for enhancing the caliber and dependability of evidence in forensic investigations.

Keywords: Artificial intelligence; Dental age estimation; Forensic dentistry; Human rights; Justice

1. Introduction

Age estimation is essential across scientific and forensic domains, including forensic medicine, anthropology, and demographic research. In scenarios like natural disasters, accurate biological age estimation is a crucial screening tool to streamline the identification process for missing individuals. Furthermore, precise age estimation at death is imperative for identifying skeletal remains in forensic anthropology. The accuracy of age estimation methodologies profoundly impacts individual identification efforts, demographic analyses, and broader human population studies. One prominent avenue for age estimation in the adult population revolves around assessing dental characteristics [1,2].

Dental components are a valuable indicator for estimating the age of an adult. However, they can be affected by various external and internal factors, leading to differences between dental age and chronological age. Since the mid-19th century, scientists have developed many ways to estimate the age of persons over 18 years old. These methods have been classified into three main approaches: morpho-histological, radiological, and biochemical analysis. The radiographic approach is a non-invasive and cost-effective approach to age estimation compared to histological and biochemical approaches. Assessing age in adults is more challenging than in children and adolescents due to the completion of dental development. Therefore, evaluating the post-formation changes and the maturation stage of third molars visible on radiographs is considered the most reliable method for establishing adult age [3–5]. Conventional dental age estimation analysis depends significantly on manual data extraction carried out by forensic odontologists.

* Corresponding author: Arofi Kurniawan

The judgment of an individual age was developed depending on the experience and knowledge of the experts. Nevertheless, this method is time-consuming and prone to subjective biases affecting the age estimation result [6].

Artificial Intelligence (AI) marks the beginning of a new era in forensic sciences. In recent years, there has been a notable increase in international research efforts utilizing AI technology in different forensic fields, such as facial recognition, age estimation, sex determination, and DNA analysis. This highlights the practicality and benefits of incorporating AI technology into forensic work. AI is a dynamic technological instrument that evolves with time, bringing new energy to forensic sciences. AI is created to mimic human intellect and is skilled at visual perception, speech recognition, decision-making, and natural language processing. Its incorporation into medicine and dentistry has been widespread, with forensic uses utilizing many approaches, including machine learning, deep learning, neural networks, and artificial neural networks. AI is crucial in improving the precision and effectiveness of analyzing adult human teeth for age estimation. AI shows potential in improving age estimates and speeding up review processes by analyzing complex patterns in human dental data. Integrating AI technology with forensic medicine is set to transform age estimation methods, enhancing forensic practice with unparalleled precision and effectiveness [7–10]. The present literature review discusses various insights into the application of AI for dental age estimation.

2. Adult dental age estimation

Dental age estimation in adults is crucial to human identification, particularly in forensic contexts and for individuals without valid identification documents. The methods for estimating adult dental age can be categorized into morpho-histological, radiological, and biochemical approaches. Morpho-histological approaches entail examining teeth, whether sectioned or unsectioned, to observe age-related regressive changes. Gustafson's approach, established in 1950, is a prominent illustration of this approach. Gustafson's technique evaluates age-related changes in teeth, including attrition, secondary dentine, periodontal recession, cementum apposition, root resorption, and dentine translucency [11].

Radiological methods use dental radiographs to estimate age non-invasively. Kvaal's technique, developed in 1995, is a radiographic method that uses the relationship between age and the size of the dental pulp to estimate age [12]. This method has been refined and applied to digital panoramic radiographs [13]. Age estimation using radiographs is challenging after age 17 due to the completion of permanent tooth eruption. Subsequently, the formation of third molar teeth can be a reliable indicator of an individual's age. The Harris and Nortje approach outlines five stages of third molar root growth and their average ages and lengths [14]. The Van Heerden technique uses panoramic radiography to evaluate the growth of the mesial root of third molars for age determination. This approach for determining dental age in humans is less invasive and does not need tooth extraction. Pulp-tooth ratio estimations have been utilized on individuals from various groups. This method analyzes linear pulp, tooth, and root length, along with root and pulp width measurements at three distinct root levels. It was first used with periapical radiography and then adapted for panoramic radiography and tomography. This method analyzes pulp and tooth area measurements using periapical and panoramic radiographs. Another approach to determining the age of adult teeth involves analyzing the ratio of pulp volume to tooth volume using CBCT radiographs [15,16].

Biochemical techniques for dental age assessment rely on the molecular alterations in durable proteins and hard tissues such as teeth and bone as part of the aging process. These approaches are especially beneficial for determining adult age when growth stops, and degenerative alterations become noticeable. Two main biochemical approaches are used for estimating dental age: aspartic acid racemization and collagen crosslinks, Advanced Glycation-End Products (AGEs), and Mitochondrial DNA Mutations. Biochemical methods offer several advantages over morphological and radiographic methods, such as being less subjective and providing more consistent results. However, further studies are needed to provide a more standardized method for dental age estimation [17].

Various factors, including the presence of dental caries, periodontal disease, and other exogenous and endogenous factors, can influence the accuracy of dental age estimation methods. Tooth wear can be an age predictor since teeth naturally erode over time. As individuals age, changes in their oral health might occur, such as root resorption, which may impact the precision of dental age estimation. In addition, the reliability of these methods can also be affected by the population being studied, as some methods may not be applicable to all population groups [4,18–20].

3. Artificial intelligence in brief

Artificial Intelligence (AI) involves developing computers, software, or robots capable of intelligent thinking like the human mind. The technique entails examining the human brain's patterns and understanding cognitive processes to create intelligent software and systems. Artificial intelligence is already essential in our everyday lives, transforming multiple sectors and improving user interactions. AI applications such as chatbots, virtual assistants, and real-time navigation systems are noteworthy examples. AI systems are created to prioritize important tasks and improve decision-making by analyzing relevant facts associated with a specific scenario. They are utilized for intricate problem-solving, pattern identification, and decision-making procedures. AI strategies are based on probability theory, economics, and algorithm design, and the field incorporates computer science, mathematics, psychology, and languages. There are several essential concepts and terms in the discussion regarding AI, including machine learning (ML), deep learning (DL), neural networks (NN), and reinforcement learning (RL) [21].

Machine learning is a branch of AI that concentrates on creating computer systems that can learn and enhance their performance based on input without requiring explicit programming. It allows software systems to see patterns and create forecasts, categorizations, or determinations using past data. ML algorithms are trained on data to discover correlations and create forecasts, and they are applicable in several areas, such as recommendation systems, fraud detection, image recognition, and natural language processing. ML is used in various industries to automate tasks, improve business operations, and enhance customer experiences. It is a complex and challenging technology that requires deep expertise and significant resources [7].

Machine learning encompasses three primary types: supervised, unsupervised, and reinforcement learning. Supervised learning entails training algorithms using labeled data to facilitate predictions or classifications. Conversely, unsupervised learning involves training algorithms with unlabeled data to discern patterns or group similar data points. Reinforcement learning, on the other hand, operates by training algorithms through iterative trial and error processes to ascertain optimal actions within a given environment. These distinct types of machine learning serve as foundational frameworks underpinning various applications across diverse domains, facilitating advancements in predictive modeling, data analysis, and decision-making processes [22–24].

Deep learning is a form of machine learning that entails constructing neural networks with numerous layers of interconnected nodes that collaborate to learn from data. Deep learning involves a computer model learning tasks through examples rather than explicit programming. The term “deep” pertains to the number of layers in the network, with a greater number of layers indicating a deeper network. Deep learning relies on artificial neural networks (ANNs), which consist of interconnected neurons that may be trained to identify input patterns. Deep learning algorithms power various artificial intelligence applications such as voice assistants, fraud detection, and autonomous vehicles. Deep learning models are taught with extensive labeled datasets and neural network structures that acquire features. Deep learning can handle organized and unstructured data like text and images. It automates feature extraction, reducing the need for human specialists. Deep learning necessitates a substantial quantity of labeled data and computational resources, proving highly advantageous for data scientists handling the collection, analysis, and interpretation of vast datasets [25,26].

Neural networks, also known as artificial neural networks (ANNs) or simulated neural networks (SNNs), are a branch of machine learning that draws inspiration from the structure and operation of the human brain. The networks are made up of interconnected layers of artificial neurons that process and send information in order to learn and make predictions. A neural network generally consists of an input layer, one or more hidden layers, and an output layer. Every node within a layer is linked to nodes in the subsequent layer by connections that possess specific weights and thresholds. Weights influence connection strength, while thresholds dictate node activation. Throughout the learning process, a neural network fine-tunes its weights to enhance its precision. Backpropagation is a technique that computes the error linked to each neuron and then modifies the weights accordingly. Neural networks are utilized in various applications, such as image recognition, natural language processing, and speech recognition. They can handle structured and unstructured data and have improved in power and efficiency due to advancements in deep learning techniques [27,28].

4. Artificial intelligence for dental age estimation

The application of AI in dental age estimation has become more commonly used to provide better accuracy and effectiveness in forensic identification. AI-aided dental age estimation can improve clinical and forensic practices by offering more precise and effective age evaluations. Many studies have employed various AI methods, including deep learning models, convolutional neural networks (CNN), and machine learning algorithms, to evaluate dental panoramic images, X-rays, and other dental data to estimate the age of individuals. The results demonstrate a high level of precision in age estimation, with certain studies obtaining accuracies as high as 90% for specific age groups [29–31].

Artificial intelligence (AI) offers valuable support in dental age estimation by scrutinizing dental imagery, including X-rays or panoramic radiographs, to gauge an individual's age through tooth development and wear assessment. Leveraging AI algorithms, patterns and features indicative of various age groups can be discerned and the system can be trained to deliver accurate age estimations. Furthermore, AI facilitates task automation, notably in dental image analysis, mitigating manual workload and enhancing the efficiency and precision of the identification process. Beyond age estimation, AI holds the potential to forecast the probability of specific dental conditions and diseases based on patient data, thus aiding in preventive measures and treatment strategies. Nonetheless, the field of AI-based age estimation in dentistry is nascent, lacking a universally accepted approach for adults with permanent dentition [7,32].

Deep Convolutional Neural Networks (DCNN) have been implemented for automatic tooth segmentation utilizing dental X-ray images, streamlining the segmentation process. This machine learning technique demonstrates superior performance compared to alternative methods. The DCNN workflow involves three primary stages: localization, segmentation, and classification of third molars. Localization entails predicting the geometric center within the original image, achieved through convolutional neural networks (CNN) such as YOLO and ImageNet, which effectively identify the radiographic location of third molars. Subsequently, radiography is combined with third molar segmentation to classify developmental stages, employing two distinct CNN architectures: a simple CNN and DenseNet201. This classification facilitates age estimation based on third molar development [30,31,33].

Implementing deep learning methods for dental age estimation presents several challenges. Firstly, there is the issue of data scarcity. Large, high-quality, and well-annotated datasets are crucial for training and validating deep learning models. However, collecting such datasets can be challenging due to the need for precise age information and the time-consuming nature of labeling images. Additionally, suboptimal training data quality can significantly impact model performance. Poorly labeled or low-quality images can lead to suboptimal training and reduced accuracy. Furthermore, fine-tuning deep learning models for optimal performance is often a complex and time-consuming process that requires expertise in machine learning and image processing. Transfer learning, another technique, may not always be effective in dental age estimation due to the unique characteristics of dental images and the complexity of the task. Moreover, generalizing deep learning models to different populations can be challenging due to variations in dental development patterns and tooth morphology, potentially reducing accuracy for certain populations. Interpretability is another concern, as deep learning models can be difficult to interpret, making it challenging to understand how the models arrive at their predictions, particularly in applications where transparency and explainability are essential, such as in forensic medicine. Finally, the use of deep learning methods for dental age estimation raises regulatory and ethical concerns regarding privacy, data protection, and the potential for technology misuse, necessitating careful consideration and regulation to ensure responsible use. Despite these challenges, ongoing research aims to address these issues and enhance the accuracy and reliability of deep learning methods in dental age estimation [34–37]

5. Conclusion

Integrating AI with dental age estimation has the potential to enhance accuracy in forensic identification. Ongoing research strives to solve hurdles such as limited data, training difficulties, and ethical considerations. Artificial intelligence, particularly deep convolutional neural networks (DCNNs), can enhance tooth analysis by automating the process, improving accuracy and efficiency. Moreover, AI assists in forecasting dental problems, contributing to their prevention and treatment. AI-driven dental age estimation for adults is still evolving and lacks a uniform technique; however, ongoing studies are focused on improving methodologies. Forensic processes can significantly improve age estimation methodologies by overcoming hurdles and utilizing AI's capabilities.

Compliance with ethical standards

Disclosure of Conflict of interest

The authors declare that they have no conflicts of interest related to the study presented in this paper.

References

[1] Kurniawan A, Chusida A, Atika N, Gianosa TK, Solikhin MD, Margaretha MS, et al. The Applicable Dental Age Estimation Methods for Children and Adolescents in Indonesia. Int J Dent 2022;2022:1–6. https://doi.org/10.1155/2022/6761476.

[2] Prakoeswa BFWR, Kurniawan A, Chusida A, Marini MI, Rizky BN, Margaretha MS, et al. Children and Adolescent Dental Age Estimation by the Willems and Al Qahtani Methods in Surabaya, Indonesia. Biomed Res Int 2022;2022:1–4. https://doi.org/10.1155/2022/9692214.

[3] Verma M, Verma N, Sharma R, Sharma A. Dental age estimation methods in adult dentitions: An overview. J Forensic Dent Sci 2019;11:57–63. https://doi.org/10.4103/jfo.jfds_64_19.

[4] Puranik M, Uma SR. Dental Age Estimation: A Review. Journal of Dental and Maxillofacial Research 2015;1:24. https://doi.org/10.31038/jdmr.2018114.

[5] Arora J, Talwar I, Sahni D, Rattan V. Secondary dentine as a sole parameter for age estimation: Comparison and reliability of qualitative and quantitative methods among North Western adult Indians. Egypt J Forensic Sci 2016;6:170–8. https://doi.org/https://doi.org/10.1016/j.ejfs.2016.05.006.

[6] Kurniawan A, Agitha SRA, Margaretha MS, Utomo H, Chusida A, Sosiawan A, et al. The applicability of Willems dental age estimation method for Indonesian children population in Surabaya. Egypt J Forensic Sci 2020;10:5. https://doi.org/10.1186/s41935-020-0179-6.

[7] Mohammad N, Ahmad R, Kurniawan A, Mohd Yusof MYP. Applications of contemporary artificial intelligence technology in forensic odontology as primary forensic identifier: A scoping review. Front Artif Intell 2022;5. https://doi.org/10.3389/frai.2022.1049584.

[8] 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;137:1117–46. https://doi.org/10.1007/s00414-023-02960-z.

[9] Vodanović M, Subašić M, Milošević DP, Galić I, Brkić H. Artificial intelligence in forensic medicine and forensic dentistry. J Forensic Odontostomatol 2023;41:30–41.

[10] Ahmed O, Saleem SA, Khan AA, Daruwala S, Pettiwala A. Artificial intelligence in forensic odontology – A review. International Dental Journal of Student's Research 2023;11:54–60. https://doi.org/10.18231/j.idjsr.2023.012.

[11] Olze A, Hertel J, Schulz R, Wierer T, Schmeling A. Radiographic evaluation of Gustafson's criteria for the purpose of forensic age diagnostics. Int J Legal Med 2012;126:615–21. https://doi.org/10.1007/s00414-012-0701-y.

[12] Kvaal SI, Kolltveit KM, Thomsen IO, Solheim T. Age estimation of adults from dental radiographs. Forensic Sci Int 1995;74:175–85. https://doi.org/10.1016/0379-0738(95)01760-g.

[13] Mittal S, Nagendrareddy S, Sharma M, Agnihotri P, Chaudhary S, Dhillon M. Age estimation based on Kvaal's technique using digital panoramic radiographs. J Forensic Dent Sci 2016;8:115. https://doi.org/10.4103/0975-1475.186378.

[14] Harris MJ, Nortjé CJ. The mesial root of the third mandibular molar. A possible indicator of age. J Forensic Odontostomatol 1984;2:39–43.

[15] Marroquin TY, Karkhanis S, Kvaal SI, Vasudavan S, Kruger E, Tennant M. Age estimation in adults by dental imaging assessment systematic review. Forensic Sci Int 2017;275:203–11. https://doi.org/10.1016/j.forsciint.2017.03.007.

[16] Limdiwala P, Shah J. Age estimation by using dental radiographs. J Forensic Dent Sci 2013;5:118. https://doi.org/10.4103/0975-1475.119778.

[17] Pillalamarri M, Manyam R, Pasupuleti S, Birajdar S, Akula ST. Biochemical analyses for dental age estimation: a review. Egypt J Forensic Sci 2022;12:2. https://doi.org/10.1186/s41935-021-00260-4.

[18] Hidayat SR, Oscandar F, Malinda Y, Sasmita IS, Dardjan M, Murniati N, et al. Human age estimation based on pulp volume of canines for chronological age estimation: Preliminary research. Padjadjaran Journal of Dentistry 2018;30:184. https://doi.org/10.24198/pjd.vol30no3.19302.

[19] Lewis JM, Senn DR. Forensic Dental Age Estimation: An Overview. J Calif Dent Assoc 2015;43:315–9. https://doi.org/10.1080/19424396.2015.12222856.

[20] Nayyar AS, Anand Babu B, Krishnaveni B, Vaishnavi Devi M, Gayitri HC. Age estimation: Current state and research challenges. Journal of Medical Sciences (Taiwan) 2016;36:209–16. https://doi.org/10.4103/1011-4564.196348.

[21] Ertel W. Introduction to Artificial Intelligence. Cham: Springer International Publishing; 2017. https://doi.org/10.1007/978-3-319-58487-4.

[22] Linardatos P, Papastefanopoulos V, Kotsiantis S. Explainable AI: A Review of Machine Learning Interpretability Methods. Entropy 2020;23:18. https://doi.org/10.3390/e23010018.

[23] Agrawal P, Nikhade P. Artificial Intelligence in Dentistry: Past, Present, and Future. Cureus 2022;14:e27405. https://doi.org/10.7759/cureus.27405.

[24] Putra RH, Doi C, Yoda N, Astuti ER, Sasaki K. Current applications and development of artificial intelligence for digital dental radiography. Dentomaxillofacial Radiology 2022;51. https://doi.org/10.1259/dmfr.20210197.

[25] Kotu V, Deshpande B. Deep Learning. Data Science, Elsevier; 2019, p. 307–42. https://doi.org/10.1016/B978-0-12-814761-0.00010-1.

[26] Chen Y, Li L, Li W, Guo Q, Du Z, Xu Z. Deep learning. AI Computing Systems, Elsevier; 2024, p. 53–121. https://doi.org/10.1016/B978-0-32-395399-3.00009-3.

[27] Yang ZR, Yang Z. Artificial Neural Networks. Comprehensive Biomedical Physics, Elsevier; 2014, p. 1–17. https://doi.org/10.1016/B978-0-444-53632-7.01101-1.

[28] Walczak S, Cerpa N. Artificial Neural Networks. Encyclopedia of Physical Science and Technology, Elsevier; 2003, p. 631–45. https://doi.org/10.1016/B0-12-227410-5/00837-1.

[29] Bjelopavlovic M, Zeigner A-K, Hardt J, Petrowski K. Forensic Dental Age Estimation: Development of New Algorithm Based on the Minimal Necessary Databases. J Pers Med 2022;12:1280. https://doi.org/10.3390/jpm12081280.

[30] Shen S, Liu Z, Wang J, Fan L, Ji F, Tao J. Machine learning assisted Cameriere method for dental age estimation. BMC Oral Health 2021;21:641. https://doi.org/10.1186/s12903-021-01996-0.

[31] Mohamed EG, Redondo RPD, Koura A, EL-Mofty MS, Kayed M. Dental Age Estimation Using Deep Learning: A Comparative Survey. Computation 2023;11:18. https://doi.org/10.3390/computation11020018.

[32] Aljameel SS, Althumairy L, Albassam B, Alsheikh G, Albluwi L, Althukair R, et al. Predictive Artificial Intelligence Model for Detecting Dental Age Using Panoramic Radiograph Images. Big Data and Cognitive Computing 2023;7:8. https://doi.org/10.3390/bdcc7010008.

[33] Pintana P, Upalananda W, Saekho S, Yarach U, Wantanajittikul K. Fully automated method for dental age estimation using the ACF detector and deep learning. Egypt J Forensic Sci 2022;12:54. https://doi.org/10.1186/s41935-022-00314-1.

[34] Bui R, Iozzino R, Richert R, Roy P, Boussel L, Tafrount C, et al. Artificial Intelligence as a Decision-Making Tool in Forensic Dentistry: A Pilot Study with I3M. Int J Environ Res Public Health 2023;20:4620. https://doi.org/10.3390/ijerph20054620.

[35] Kim S, Lee Y-H, Noh Y-K, Park FC, Auh Q-S. Age-group determination of living individuals using first molar images based on artificial intelligence. Sci Rep 2021;11:1073. https://doi.org/10.1038/s41598-020-80182-8.

[36] Khanagar SB, Vishwanathaiah S, Naik S, A. Al-Kheraif A, Devang Divakar D, Sarode SC, et al. Application and performance of artificial intelligence technology in forensic odontology – A systematic review. Leg Med 2021;48:101826. https://doi.org/10.1016/j.legalmed.2020.101826.

[37] Kahm SH, Kim J-Y, Yoo S, Bae S-M, Kang J-E, Lee SH. Application of entire dental panorama image data in artificial intelligence model for age estimation. BMC Oral Health 2023;23:1007. https://doi.org/10.1186/s12903-023-03745-x.