Dental Age Assessment

A Global Perspective

Aman Chowdhry
Priyanka Kapoor
Editors

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Preface

The lack of an extensive, internationally applicable reference on dental age assessment in the field of forensic odontology was identified as a gap in the literature, which gave rise to the concept for this book. It was becoming more and more obvious that a special volume on dental age estimation was necessary following the success of our earlier work, *Handbook of Forensic Odontology: A Global Perspective* (2018). With collaboration from leading scientists across the globe, we provide *Essentials of Dental Age Assessment: A Global Perspective*—a work influenced by multidisciplinary insights and international expertise.

We would like to sincerely thank the Springer Nature production team for their dedication, professional support, and direction in making this book a reality. Their work has been crucial in shaping this book into a polished and accessible academic resource.

This book covers a wide range of age estimation methodologies, from prenatal to adult stages, while integrating classical and contemporary approaches. It is intended to be both academically rigorous and easily readable. In order to enhance student learning, each chapter includes multiple-choice questions (MCQs), mind maps, and well-illustrated graphics. In-depth discussions are held on cutting-edge subjects including DNA methylation, artificial intelligence, and radiocarbon dating, as well as conventional methods like the London Atlas and Camariere techniques.

In an effort to put knowledge into practice, the book also highlights the usefulness of age assessment through report writing that is supported by literature. With contributions from all around the world and an approachable structure, this book hopes to become a fundamental resource for forensic odontology researchers, practitioners, educators, and students everywhere.

In addition to being a trustworthy companion in forensic and academic contexts, we hope that this volume makes a significant contribution to practice and learning.

New Delhi, India

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16.1 Introduction

The increasing number of undocumented or irregular migrants has raised concerns, particularly in third-world countries. The biological profile, which provides vital bone demographic information such as age, is a critical piece of evidence for authorities when determining refugee status and sentencing criminals. In cases involving deceased bodies, this information allows for the narrowing down of missing persons' lists and positive or definitive identification of unidentified human remains.

Traditionally, age estimation relies on conventional radiographic examinations and human competence. Demirjian's technique, amongst others, is frequently used to establish an individual's age, where it involves manually rating all seven permanent mandibular teeth using panoramic dental imaging and a designated atlas. However, this method becomes significantly lagging during large-scale incidents, leading to increased workloads and extended working hours. This leads to delayed identification and thus imposes pressure on the authority and the next-of-kin. Moreover, the conventional method may introduce subjective interpretation bias, especially between young and experienced forensic odontologists.

To address these limitations, researchers have explored the use of artificial intelligence (AI) technology to estimate an individual's sex and age based on radiographic images. AI is seldom addressed as automation. By definition, AI is the

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ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings. The term is frequently applied to the project of developing systems endowed with the intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize, or learn from past experience.

Automation on the other hand, especially in health care, means using software that makes care and services better. In addition, for the sake of efficiency, this technology makes use of modern techniques and tools. It helps us monitor the safety, security, and health status of our family members. The automation system may benefit both healthcare services and patients. For example, in healthcare services, the automation system improved the operational and administrative areas [8]. The impact of automation includes faster data retrieval, improved ordering, and quicker billing.

Furthermore, early disease identification, greater precision and speed in medical diagnostics, superior and long-lasting technology, and potentially reduced errors are some of the primary benefits of health care automation for patients [3]. The sophisticated healthcare system has the potential to improve efficiency and uniformity significantly. This indicates that an automation system built and adapted from the traditional way performs well. Besides, automation may aid in the improvement of reproducibility especially in the automated age estimation system [30]. Through the learning process, the ideal dataset for training can reach a complete agreement between inter-rater observers. Technically, a larger dataset for training can boost an automated system's performance significantly.

Age estimation in children and adolescents often depends on morphological methods, such as radiological examination of skeletal and dental development. However, the pelvic bone is one of the best indicators of adult age, and cranial sutures are also good predictors of death age. As the standard way of estimating age usually refers to the "gold standard," this shortcoming has become one of the possible research areas for automating the method.

One of the earliest studies on the automated dental age estimation method was based on a computer vision application, which uses the image segmentation approach to segment the region of interest (ROI) to estimate dental age in adults. The development of automated line-by-line scanning of tooth-cementum annulations (TCA) software to assess an individual's age was presented where this approach was evaluated on an unknown individual's age and compared to manual TCA counting-based age estimation. However, no comparison results were reported by the authors [7]. The advancement of computer vision and artificial neural network technology enables interdisciplinary scholars to improve reproducibility in a wide range of dental applications, particularly the operator-dependent procedure.

16.2 Application

The AI, machine learning (ML), and deep learning (DL) have become the most talked-about technologies in today's business sector, as corporations use these advancements to create intelligent devices and apps. It could be used as a second opinion for clinicians in the health industry, assisting them with clinical diagnosis and treatment.

AI is used informally when a machine mimics “cognitive” functions that humans associate with other human minds, such as “learning” and “problem-solving.” Machine learning, on the other hand, was defined by Munoz [25] as the branch of computer science that can learn without being explicitly programmed. Machine learning is the study and creation of algorithms that can learn from data and make predictions based on that data. Meanwhile, deep learning is a branch of machine learning that emphasizes algorithms that are inspired by the structure of the human brain. This system can handle massive amounts of structured and unstructured data.

Convolutional neural networks (CNN) are the prime example of DL. The architecture of CNN typically consists of convolutional, pooling, and fully connected layers. Figure 16.1 shows an example of the general architecture of CNN, which consists of two layers of both convolution and pooling. Studying successful applications is an excellent way to create effective CNN architectures. The LeNet-5 is often described as the first successful and important application of CNNs before the ImageNet Large Scale Visual Recognition Challenge or ILSVRC. The intense study and application of CNNs from 2012 to 2016 for the ILSVRC witnessed four different winning architectural innovations: AlexNet, VGG, Inception, and ResNet.

LeNet-5 [19] was probably the first CNN that was widely known and worked well. It was created to address the issue of handwritten character recognition. The system was tested on the MNIST standard dataset, attaining a classification accuracy of 99.2% (or a 0.8% error rate). The network was then defined as the key component of a larger system known as graph transformer networks. According to this paper, the CNN architecture has seven layers and inputs grayscale images with the shape 32 × 32, which corresponds to the size of images in the MNIST dataset.

On the other hand, AlexNet [18] could be credited with bringing back interest in neural networks and paving the way for deep learning to become the best way to do many computer vision tasks. The model was first made for the ILSVRC-2010 competition, in which people had to put pictures of things into thousands of different groups. The architecture of this model consists of five convolutional layers in the feature extraction section, in which the authors fixed the input images to a size of

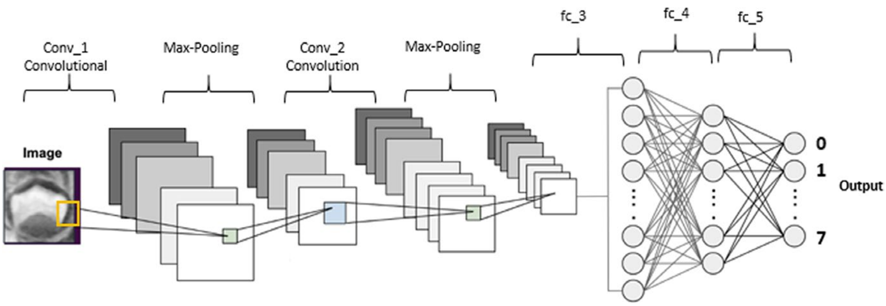

Fig. 16.1 Example of CNN architecture

224 × 224 with three colour channels. In contrast, the classifier section has three fully connected layers.

Another excellent intervention was published in 2014 called "Very Deep Convolutional Networks for Large-Scale Image Recognition," which aimed to standardize architecture design for deep CNN while also developing significantly deeper and better performing models [33]. VGG is the abbreviation for the Visual Geometry Group at Oxford, which is where they developed their architecture. For the ILSVRC-2014 competition, the VGG model was created. The employment of a large number of small filters is the first significant change that has established a genuine standard. Filters of sizes 3 × 3 and 1 × 1 with a stride of one, as opposed to the huge-sized filters in LeNet-5 and the smaller but still very large filters with a stride of four in AlexNet. The VGG models' design decisions have been the essential foundation and have become the starting point for simple and straightforward CNNs. In addition, the network architecture of the VGG model uses multiple convolutional layers stacked together before a max-pooling layer is used.

Instead of a simple and straightforward CNN, Szegedy et al. [35] show that a deeper parallel convolutional layer is a big step forward in how convolutional layers are used. It was suggested to use the inception architecture, and a model called GoogLeNet did very well in the ILSVRC-2014 competition. This model has a block of parallel convolutional layers with varying-sized filters such as 1 × 1, 3 × 3, 5 × 5, and 3 × 3 max-pooling layers, in which the outputs are then combined. This model was considered an intense and profound one as it has 22 layers.

Another significant advancement of the CNN model was the Residual Network (ResNet) [14] which has 152 layers. The model's development is based on the idea of residual blocks that use shortcut connections. A residual block is a pattern made up of two convolutional layers with ReLU activation. The output of the block is added to the input of the block. Basically, this model is inspired by the VGG model network. The idea is that the authors take exactly what is being proposed in the VGG network. However, no pooling layers between blocks were designed, resulting in a plain network. To define residual blocks, the plain network is transformed into a residual network by adding shortcut connections. The shortcut connection's input is usually the same size as the residual block's output.

The CNN model was one of the frequent network architectures for DL used in the field of dentistry, especially for the application of human identification that focuses on age estimation [11]. The abovementioned models are based on the CNN model, which at the beginning of its production only had a few layers of complexity that got more complicated and sophisticated as more inventions were made. The CNN is particularly useful for finding patterns in images to recognize objects, classes, and categories. It will learn directly from data. Because dental x-rays are a great diagnostic tool that is commonly used for diagnosis and treatment planning, the majority of the data was in images, and CNN is more advantageous than other traditional machine learning models because it can learn all the data through patterns and provides high reproducibility.

16.3 Previous Research in Age Estimation

The automation process of age assessment demonstrated exact reproducibility, just like the traditional method. The incomparability between the two methods, conventional and automated, was usually due to their different types of features. For example, if continuous features such as area and volume of anatomical structures are considered and the ROI is detected automatically, human observer action cannot compare to the automated staging system [9]. Therefore, only the performance of age estimation methods can be compared.

In 2015, Ge et al. [12] proposed a semi-automated system based on the volumetric measurements of the pulp/tooth chamber of the first molar. An open-source 3D image semi-automatic segmenting and voxel-counting software, ITK-SNAP 2.4, is used to calculate the volume of the pulp chamber. Logarithmic regression was used to estimate age using the volume obtained from the calculation using the software. In addition, the authors did the same study, but volumetric measurement was done on the 13 tooth types. Based on their findings, the authors discovered that the upper second molar volume is the most correlated with age [13].

Meanwhile, Asif et al. [4] studied a correlation between chronological age and pulp/tooth volume ratio for Malaysian adults, where two volumetric analysis methods of maxillary central incisors were employed. Method 1 used volumetric measurement of the pulp cavity/tooth ratio, and Method 2 used volumetric analysis of the pulp chamber/crown ratio. The authors used mimic software to process the images acquired from CBCT scans. Based on their findings, both methods show a strong correlation between chronological age and pulp/tooth volume ratio. On the other hand, method 2 yielded a better coefficient of determination value ($R2 = 0.78$) than method 1 ($R2 = 0.64$). In addition, an automated system that involves no human intervention during the preprocessing phase in Method 2 shortens the process and exhibits higher interobserver reliability. The authors also proposed using the method 2 regression equation in age estimation. Based on the studies above [4, 12, 13, 34], all of them used continuous data, such as the volume of the pulp chamber, to perform the dental age estimation, but none of them did a study on the development of the dentition.

The most common method of dental age estimation, which is based on tooth development, is based on Demirjian's staging system [10] where this method uses digital panoramic dental imaging to estimate the chronological age of an individual based on the mineralization of seven left permanent lower teeth. This method is also suitable for determining dental maturity states in individuals with known ages, rather than predicting an unknown age.

Several methods have been used in the past to segment dental radiographic images with good results. A semi-automatic approach which is based on a contour extraction method in order to overcome the limitation of fuzzy tooth contours caused by the low image quality has been proposed by Jain and Chen [16]. It involved three stages: image segmentation, pixel classification, and contour matching. Results showed that the proposed method can produce promising object segmentation using small sets of data. However, further improvement is needed as the algorithm had difficulties working on the blurry image, occluded objects, and irregular shapes of teeth that eventually led to the oversegmentation problem.

Another semi-automatic approach has been discussed by Banumathi et al. [5], which also involves three stages: morphological contour detection, Gaussian filtering, and an existing semi-automatic contour extraction method. Results affirmed that the proposed algorithm could achieve a precision rate of 0.7. However, the algorithm faced the same limitation as what has been proposed by Jain and Chen [16] when the blurry input image with the occluded object is used. Tuan et al. [37] proposed a new advanced approach in which the authors presented a new semi-supervised fuzzy clustering algorithm known as SSFC-FS based on Interactive Fuzzy Satisficing. The algorithm was tested on 56 dental radiographic images and was proven to produce better clustering results compared to other methods such as Fuzzy C-Means, Otsu, eSFCM, SSCMOO, FMMBIS, and another version of SSFC-FS with the local Lagrange method known as SSFC-SC.

A fully automated system for person identification using dental radiographic images requires a prior segmentation of the images into sections containing a single tooth. Dental shape extraction based on contour information is a common approach for feature extraction. Pushparaj et al. [29] used the integral intensity projection to segment the upper jaw, lower jaw, and individual teeth separately, followed by the shape extraction based on the fast connected component. The final stage includes the distance measurement using the Mahalanobis distance equation to measure the means of the matching distance. Results showed that the algorithm has produced better performance compared to their previous work, which is based on semi-automatic contour extraction [28]. An improvement of contour extraction has been made by Lin et al. [21], who used the point reliability measuring method and calculated the Hausdorff distance (HD) between the contours. Experimental results showed that this approach can achieve 100% accuracy for single tooth segmentation.

Another fully automated segmentation approach that is based on a thresholding method for dental age assessment has been proposed by Ahmad et al. [1]. The primary goal of this method is to optimise the threshold value, T, for use with the mean, median, and OTSU thresholding methods. Choosing the right value of T will produce a good segmentation result where the foreground and background image can be effectively separated. Meanwhile, a fundamental study on the region-based segmentation approach has been discussed by Razali et al. [31], where the comparison between the Canny and Sobel methods has been made in order to fulfil the requirements of the Demirjian method for assessing all of the tooth types in quadrants 2 and 3. Besides, the application of pixel-based image segmentation associated with the mathematical morphological operation for object extraction has been proposed by Amer and Aqel [2]. The result showed that the proposed method is able to produce the lowest mean absolute error (MAE) compared to other existing methods [26].

De Tobel et al. [9] proposed an automated technique for age estimation based on the mandibular third molar development using panoramic radiographs by employing pattern recognition and classification approaches to the target images. First, image contrast is being normalized for all data and ROIs which indicate the third molar was cropped using the Photoshop software. The performance of the CNN classifier was then evaluated in a five-fold cross-validation scenario, using different validation metrics to obtain the accuracy, Rank-N recognition rate, mean absolute difference, and linear kappa coefficient. As a result, the proposed method is able to stage lower third molar development according to staging by human observers. However, more data training is required as the pilot study was only tested on 20 images.

Muad et al. [24] have proposed a contour-based segmentation method to segment the second molar teeth. This has been accomplished by measuring the ratio of the mean and standard deviation of directional image derivatives over an entire closed contour boundary using the active contour algorithm. As a result, the authors obtained an overall segmentation accuracy of 95.3%.

Apart from that, the application of digital image processing on dental radiographs is broad and extensively used for dental disease detection, quantification of dental images, and detection of the dentition structure. Image classification techniques include image sensors, image pre-processing, object detection, object segmentation, feature extraction, and object classification. Yu [39] performed the teeth classification using the CNN classifier to classify all 28 permanent teeth by excluding the third molar. The training image was tested on two different CNN models, which are 4-layer and 16-layer. The result shows that the training time for the 4 layers of the CNN model was shorter, but the accuracy was lower than for the 16 layers of the CNN model.

The CNN algorithm was used by Prajapati et al. [27] to come up with a way to classify dental diseases. The dataset consists of 251 Radio Visiography (RVG) X-ray images that were trained using the CNN model to separate three different disease severity classes. The overall accuracy obtained is very promising. A similar study was also performed by Imangaliyev et al. [15] and Choi et al. [6], where the authors implemented the CNN to detect the dental plaque and carried out quantitative light-induced fluorescence (QLF) images and dental radiographs, respectively. Both results shown are encouraging. In addition, to evaluate the quality of the dental treatment, the CNN classifier is also applied by Yang et al. [38]. As a result, the F1 score of 0.749 is obtained, which is comparable to the performance of expert dentists and radiologists.

Recently, the deep learning convolutional neural network (DCNN) has been introduced to perform automated tooth segmentation, where these artificial intelligence methods have shown better performance compared to other mathematical approaches. De Tobel et al. [9] proposed a pilot study in which they modified the pre-trained model of the AlexNet network to stage lower third molar development on panoramic radiographs for age estimation. However, improvements have been made by Merdietio Boedi et al. [22], who use the DenseNet201 network for automated stage allocation. Based on the improvement, the authors made a new hypothesis that segmenting only the third molar could further improve the automated stage allocation performance. Another recent approach utilizing the region-based convolutional neural network, which required object segmentation before the classification, has been proposed by Lee et al. [20] and Kahaki et al. [17]. Image segmentation before classification might be needed for certain conditions, especially in dental age estimation, as literature states that the variation of the third molar might affect the accuracy of age estimation in different populations Tafrount et al. [36]. As such, for the automated approach, the classification accuracy may also be affected due to the morphology of the tooth and its surroundings. According to Merdietio Boedi et al. [22], the unwanted ROIs such as periodontal ligaments, bony structures, and the mandibular nerve canal influence the performance of automated stage allocation.

Also, the review article by Sharifonnasabi et al. [32] says that there will have to be a big change towards automated procedures. Image processing, feature extraction, image categorization, decision-making, and results are common processes in the reviewed studies. However, there is no good way to determine how old the dental age is because different studies use different methods to analyse and process images. As a result, recent AI technology, which provides a better end-to-end machine learning platform with a high-level API (application programming interface), enables AI practitioners to develop potential machine learning architectures, particularly based on the CNN model.

Transfer learning or modelling from scratch can be used to train the CNN or deep learning model. Seeing a lot of real-world problems, making much bigger datasets, and testing them with a model that has already been trained does not always lead to better results on the target tasks. The other alternative is to train a model from scratch, where the random weight initialization occurs in the early operations. The advent of deep learning platforms like Tensorflow makes it easier to build our own model based on real-world problems.

Mohammad et al. [23] developed their own deep CNN model from scratch using Tensorflow and Keras and compared the findings with the conventional method of estimating the individual's age. The performance of the proposed model is promising, as 97.74% and 78.13% of training and testing accuracy were obtained, respectively. In addition, moderate agreement (Kappa value = 0.58) between the human observer and the computer was identified. Nonetheless, a robust DCNN model was achieved, as there is no sign of the model's over- or under-fitting upon the learning process.

16.4 Conclusion and Future Research

In neural networks, the architecture is all that matters. A good performance of the neural network in making a prediction will significantly improve the classification accuracy and the inter-observer agreement. Deep learning approaches have been a major success due to their ability to learn task-specific feature representations automatically. It is one of the most often utilized models in data science applications today. It is also shown to be a successful model in various fields, including pictures, text, and voice and music. As the application of deep learning grows, applying it rapidly and being scalable becomes more important. Essentially, training the CNN model can be accomplished through transfer learning or modelling from scratch, and in certain real-world problems, the performance of the CNN model built from scratch outperformed that of transfer learning or vice versa.

Instead of focusing on the primary tool, which in the majority of the reviewed literature is the orthopantomogram obtained from the dental X-ray machine, other advanced imaging modalities such as cone-beam CT and MRI can be useful. Also, most of the proposed automated systems for figuring out a person's age use Demirjian's method, which looks at the eight stages of tooth growth. Demirjian's method is undeniably exceptional. This gold standard has been verified with numerous population-specific reference datasets. Also, this method is still relevant in the research area and is being employed and used as a benchmark for the newly proposed method of dental age estimation. Another recently established atlas on dental age estimation, which estimates the dental age based on tooth development and eruption and is known as the London atlas, provides a promising outcome. Thus, considering extending the deep CNN method with the London Atlas in the future might open a new topic of research interest that may gain the attention of interdisciplinary researchers.

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