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Dental age estimation using a convolutional neural network algorithm on panoramic radiographs: A pilot study in Indonesia

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ABSTRACT

Purpose: This study employed a convolutional neural network (CNN) algorithm to develop an automated dental age estimation method based on the London Atlas of Tooth Development and Eruption. The primary objectives were to create and validate CNN models trained on panoramic radiographs to achieve accurate dental age predictions using a standardized approach.

Materials and Methods: A dataset of 801 panoramic radiographs from outpatients aged 5 to 15 years was used. A CNN model for dental age estimation was developed using a 16-layer CNN architecture implemented in Python with TensorFlow and Scikit-learn, guided by the London Atlas of Tooth Development. The model included 6 convolutional layers for feature extraction, each followed by a pooling layer to reduce the spatial dimensions of the feature maps. A confusion matrix was used to evaluate key performance metrics, including accuracy, precision, recall, and F1 score.

Results: The proposed model achieved an overall accuracy, precision, recall, and F1 score of 74% on the validation set. The highest F1 scores were observed in the 10-year and 12-year age groups, indicating superior performance in these categories. In contrast, the 6-year age group demonstrated the highest misclassification rate, highlighting potential challenges in accurately estimating age in younger individuals.

Conclusion: Integrating a CNN algorithm for dental age estimation represents a significant advancement in forensic odontology. The application of AI improves both the precision and efficiency of age estimation processes, providing results that are more reliable and objective than those obtained via traditional methods. ***(Imaging Sci Dent 2025; 55: 28-36)***

KEY WORDS: Artificial Intelligence; Age Determination by Teeth; Forensic Dentistry; Human Rights; Tooth Eruption

Introduction

Forensic odontology plays a crucial role in age estimation for legal, forensic, and humanitarian purposes. Accurate age estimation is essential in contexts such as identifying human remains, assessing age in immigration cases, and supporting criminal investigations. Dental age estimation is primarily based on evaluating tooth development and eruption stages in children and adolescents using radiographic imaging.[1] Techniques for dental age estimation in children generally fall into 3 main categories: dental atlases, tooth scoring systems, and tooth measurements. These methods are widely used due to the strong correlation between dental and chronological ages, which enhances their forensic applicability.[2-5] However, challenges such as lim-

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ited accuracy, methodological complexity, observer bias, and the time-intensive nature of these techniques remain significant concerns.[6-9]

The London Atlas of Tooth Development, introduced by AlQahtani et al.,[10] provided the foundation for the algorithm developed in this study. This atlas-based method assesses tooth development and alveolar eruption patterns via panoramic radiographs, ensuring consistency and comparability across studies. Previous research has demonstrated the reliability of this method for estimating age in the Indonesian population.[1,11-13] However, the conventional application of the AlQahtani method relies heavily on the expertise and interpretative skills of forensic odontologists, which can introduce subjectivity and variability. Furthermore, manually estimating age from a single panoramic radiograph is often complex and time-consuming in both forensic and clinical practice.[14]

The integration of artificial intelligence (AI), particularly convolutional neural networks (CNNs), represents a significant advancement in overcoming challenges associated with dental age estimation. CNNs, a sophisticated subset of deep learning models, excel at analyzing images and detecting complex patterns, making them especially suitable for interpreting detailed medical images such as dental radiographs.[15] By automating the analysis of large datasets, CNNs improve the efficiency and speed of age estimation while reducing the subjective bias inherent in human interpretation, thus yielding more consistent and reproducible outcomes. Their ability to detect intricate patterns in dental development - often beyond human recognition - further increases the precision and reliability of forensic age estimation.[16-18]

The structured methodology of the AlQahtani approach for assessing tooth development aligns effectively with AI systems. By training CNNs on extensive radiograph datasets annotated using the AlQahtani method, models can autonomously analyze dental images and generate accurate age estimations. Although CNNs have achieved remarkable success in various domains of medical image analysis, their application in forensic odontology - specifically for age estimation using the AlQahtani method - remains an emerging and promising field of research. This innovative approach holds significant potential for enhancing the precision and reliability of age estimation in forensic investigations.[19-21]

This study employed CNNs to automate the age estimation process based on the AlQahtani method for several reasons. Unlike chronological age, the AlQahtani method focuses specifically on dental parameters, making it more relevant to the study's objectives. The London Atlas of Tooth Development is a well-established framework designed to estimate age from tooth development and alveolar eruption. The primary goal was to develop and validate CNN models trained on panoramic radiographs to achieve accurate and biologically relevant age predictions. Additionally, the study aimed to enhance forensic methodologies by integrating these advanced techniques, thereby producing more objective and reliable age estimation outcomes.

Materials and Methods

Study preparation

This study received ethical approval from the Ethical Clearance Commission of the Dental Hospital at Universitas Airlangga (permit number: 41/UN3.9.3/Etik/PT/2022). A total of 801 panoramic radiographs were analyzed, collected from outpatients aged 5 to 15 years who visited Airlangga University Dental Hospital between 2019 and 2022. The inclusion criteria required high-quality panoramic radiographs accompanied by complete information, including age and sex. Radiographs displaying orthodontic appliances, prostheses, or any pathological conditions were excluded. This rigorous selection process ensured the reliability and accuracy of the dataset for developing and validating the CNN model used in this study.

This study employed a computer system with the specifications detailed in Table 1 to support the development and implementation of the CNN algorithm and the dental age estimation application. The algorithm and application were developed using Visual Studio Code and Python 3.9.12. Additionally, a user-friendly interface (Fig. 1) was designed to enhance accessibility. A user acceptance test was conducted using functional black-box testing methods to ensure that the application met user expectations and functioned correctly.

Image preprocessing

Extracting the region of interest (ROI) was crucial to ensure that the CNN model was trained on the most relevant features for dental age estimation. The process involved manually cropping the panoramic radiographs using image processing software to isolate the right quadrants of the dental arches. The cropped images were then compiled to create a training dataset, serving as the foundation for the CNN algorithm's learning process. To maintain consistency, all images were converted to ".jpg" format and resized to a standardized resolution of 128 pixels upon entry into the database. These preprocessing steps were essential for ensuring uniformity across the dataset and increasing the reliability of the training and validation processes for the machine learning models.

The CNN algorithm for dental age estimation was developed based on the London Atlas of Tooth Development framework by AlQahtani et al.,[10] which was chosen over chronological age due to its proven reliability in estimating dental age across various populations, including the Indonesian population.[2,12,13,22-25] Eleven age groups were defined for data training based on the midpoint ages outlined in the London Atlas of Tooth Development (Fig. 2). The labeling process involved estimating ages using the AlQahtani method, which was subsequently used for both training and validation. To ensure accuracy and consistency, a forensic odontologist performed the data labeling process twice at a 1-week interval. This approach minimized potential variability and enhanced the reliability of the dataset used for training the algorithm.

Given the limited dataset of 801 panoramic radiographs, data augmentation techniques were implemented before initiating the image classification process. Augmentation was achieved through rotational transformations, with images rotated incrementally by 1, 2, and 3 degrees in both clockwise and counterclockwise directions. This strategy expanded the dataset to 1,298 images, ensuring a uniform distribution across age groups with each group containing 118 images. This augmentation approach not only increased the dataset size but also improved the balance and representation across age categories, thereby enhancing the robustness and generalizability of the machine learning models. It effectively addressed challenges posed by limited and imbalanced data, contributing to more reliable model performance.

To evaluate the accuracy and generalizability of the model, 30% of the images were allocated to a validation set. This approach was essential for assessing the CNN's performance on unseen data, thereby ensuring the robustness and reliability of the dental age estimation model. A comprehensive schematic of the research workflow is presented in Figure 3, providing a visual depiction of the methodology employed in this study.

Table 1. The detailed specifications of the computer utilized to develop the dental age estimation algorithm and application

Processor	Intel® Core™ i5-3427U
CPU	CPU@1.80 GHz 2.30 GHz
RAM	4.00 GB
Operating System	Windows 10 Pro
Required software	Visual Studio Code
Programming language	Python 3.9.12

Convolutional process

This study utilized a 16-layer CNN architecture implemented with Python, TensorFlow, and the Scikit-learn library. The model comprised 6 convolutional layers responsible for feature extraction from the input images, with each convolutional layer followed by a pooling layer designed to progressively reduce the spatial dimensions of the feature maps. The final classification step employed the softmax activation function to predict class probabilities.

Several hyperparameters were fine-tuned to optimize the model's performance. Data augmentation techniques, including rotation, were applied to increase the variability

Fig. 1. User interface of the dental age estimation application developed in this study.

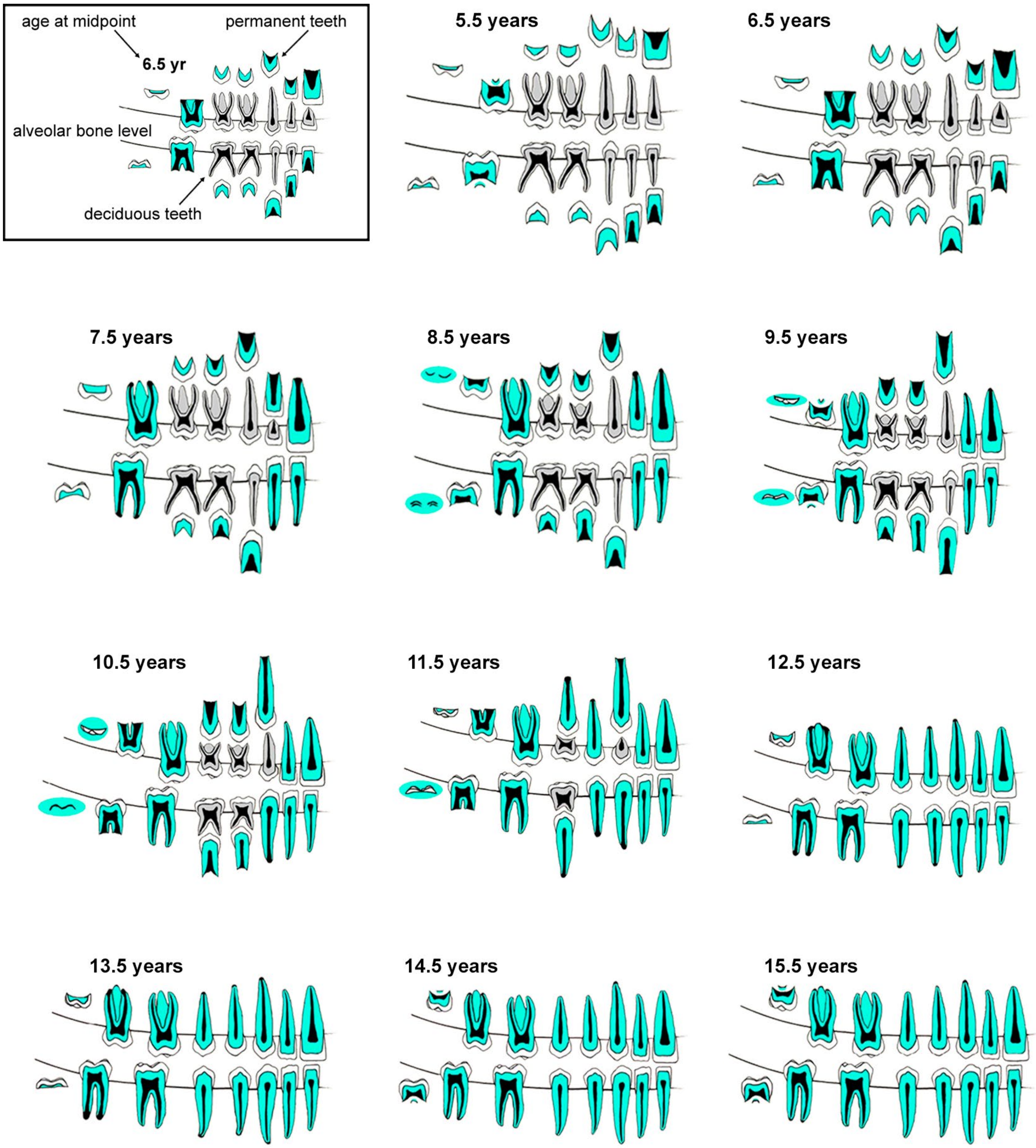

Fig. 2. Illustration of the age group classification based on the London Atlas of Tooth Development and Eruption (modified from AlQahtani et al.[10]).

and robustness of the training dataset. Additional hyperparameters, such as the kernel size in the convolutional layers, the number of filters, and the learning rate, were adjusted to control the rate at which the model's weights were updated during training.

The CNN algorithm employed convolutional kernels of varying sizes applied sequentially to extract features from the input images. Each convolutional layer consisted of multiple filters that processed pixel dimensions, capturing spatial hierarchies and patterns across the images. This process enabled the model to identify and learn new features during training. After resizing the images for uniformity,

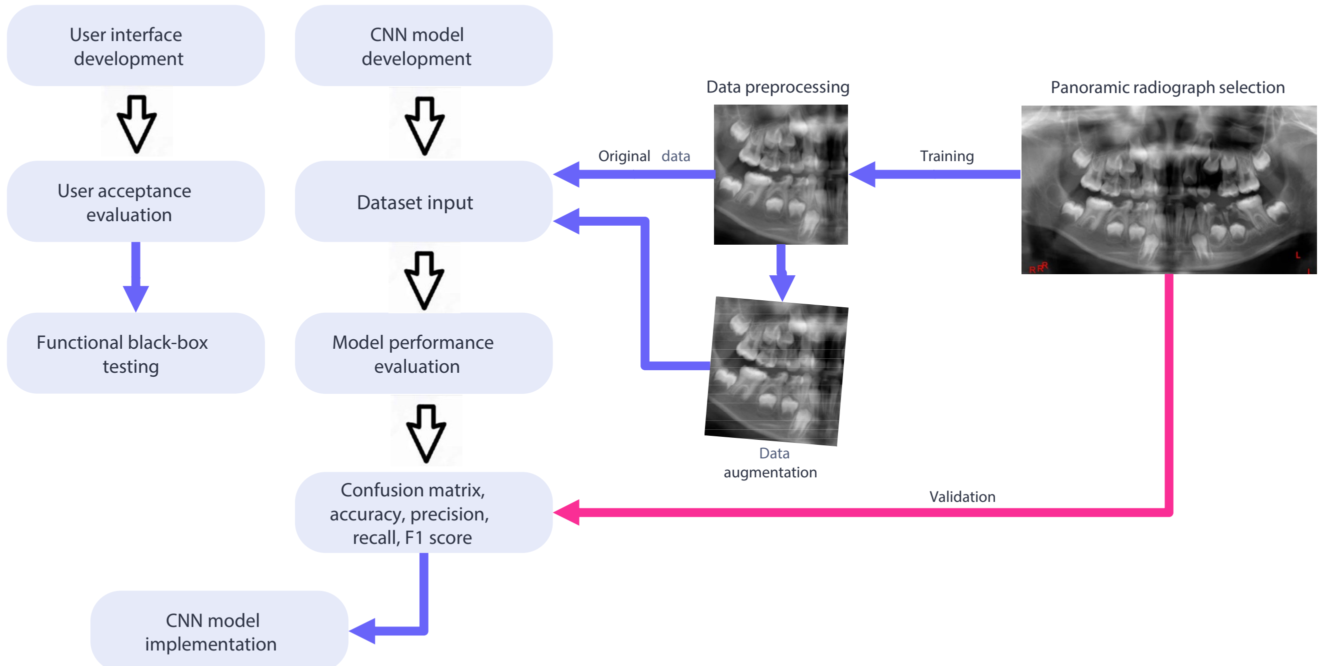

Fig. 3. Detailed schematic workflow of the present study.

convolution operations were performed to generate these features. The extracted features were then refined through a training phase repeated over 30 epochs to optimize the model's performance. Upon completion of training, the resulting model was automatically saved in a designated folder for later validation.

This iterative process ensured that the model effectively learned and stored critical patterns within the dataset. The saved model, containing the newly acquired feature set, was readily available for validation and testing, thereby improving its generalizability and accuracy for future applications.

Performance evaluation

The model's performance was systematically evaluated using a confusion matrix, which facilitated the measurement of essential metrics, including accuracy, precision, recall, and F1 score. Accuracy indicates the overall correctness of the model's predictions.

Results

Evaluation of study preparation

The user interface was designed to provide convenient access to data and information about the model's precision, estimated processing time, and prediction outcomes. Functional black-box testing was conducted to evaluate the efficiency and user-friendliness of the interface. This testing approach focused on assessing the system's functionality based on specific inputs and outputs without examining the internal code structure.[26] Through this method, the consistency and reliability of the user interface were systematically evaluated to ensure it accurately displayed expected outcomes and performed as intended. This process was critical in ensuring that users received precise and relevant information when interacting with the software.

The data labeling process was carried out by a forensic odontologist in 2 separate sessions, spaced 1 week apart, during the image preprocessing phase. To assess inter-examiner agreement, the Cronbach's alpha test was performed, yielding a coefficient greater than 0.8. This result indicates good consistency between the 2 labeling sessions and suggests that the forensic odontologist's assessments remained stable and reliable over time.

Accuracy, precision, recall, and F1 score analysis

The performance of the CNN model in dental age estimation was rigorously evaluated using key metrics such as accuracy, precision, recall, and F1 score derived from the confusion matrix. This matrix provides a detailed analysis of the model's predictions by categorizing outcomes into true positives (TPs), true negatives (TNs), false positives (FPs), and false negatives (FNs). TPs represent instances where the AI-predicted dental age correctly matches the es-

Table 2. Precision, accuracy, recall, and F1-score of the convolutional network model for dental age estimation based on the AlQahtani method

Age group	Before augmentation			After augmentation		
	Precision	Recall	F1-score	Precision	Recall	F1-score
5.5	67%	64%	65%	82%	62%	71%
6.5	47%	50%	48%	56%	61%	58%
7.5	39%	59%	47%	64%	85%	73%
8.5	57%	34%	43%	76%	74%	75%
9.5	49%	56%	52%	68%	66%	67%
10.5	14%	20%	16%	76%	90%	83%
11.5	17%	5%	7%	74%	78%	76%
12.5	29%	38%	33%	90%	76%	83%
13.5	20%	25%	22%	74%	70%	72%
14.5	42%	44%	43%	70%	87%	78%
15.5	0%	0%	0%	88%	66%	75%
Accuracy		41%			74%	

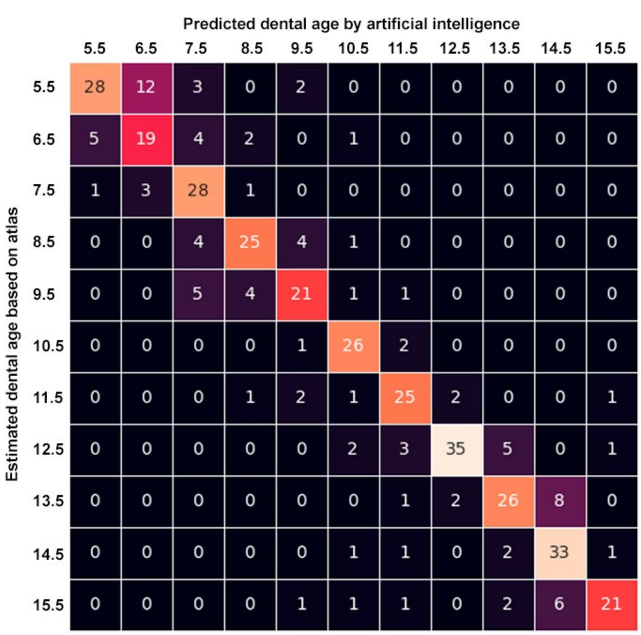

Fig. 4. Confusion matrix of dental age estimation model validation using 389 panoramic radiographs.

timated dental age based on the Atlas within the evaluated age group, while TNs reflect correct matches outside the group. FPs occurred when the model overestimated dental age, and FNs arose from underestimation.

Precision reflects the proportion of TPs relative to the sum of TPs and FPs, commonly referred to as the positive predictive value (PPV) in medical contexts. Recall, or sensitivity, measures the model's ability to correctly identify relevant instances, calculated as the ratio of TPs to the sum of TPs and FNs; this is also known as the negative predictive value (NPV). The F1 score balances precision and recall to provide a comprehensive measure of the model's performance. A model is considered highly predictive when both PPV and NPV approach 100%.

In this study, the CNN model's performance, as measured by precision, recall, and F1 score, varied significantly across different age groups, both before and after data augmentation (Table 2). Initially, the highest precision (67%) and recall (64%) were observed in the 5.5-year age group. Following augmentation, precision in this group improved substantially to 82%, although recall slightly declined to 62%, resulting in an F1 score of 71%. The 12.5-year age group recorded the highest precision (90%) post-augmentation, while the 10.5-year age group demonstrated the highest recall. Overall, the model's performance improved markedly, with the average F1 score increasing from 34% to 74% and overall accuracy rising from 41% to 74%.

Validation of the model, conducted using 389 panoramic radiographs, revealed the highest accuracy in the 12.5-year age group. In contrast, the 6.5-year age group exhibited the highest misclassification rate (Fig. 4). These findings highlight variability in the model's performance across different age groups and identify specific areas that may require further refinement and optimization.

Discussion

Radiographic and tomographic techniques are widely recognized for their cost-effectiveness and essential role in forensic odontology, particularly when integrated with advanced information technology. These imaging methods provide accurate age estimation, which is vital for identifying individuals in forensic investigations. They offer a reliable means of assessing age-related changes in dental structures.[27] Professionals in both clinical and forensic odontology must possess a thorough understanding of these imaging techniques and their legal applications to ensure accurate and legally sound age determinations—a fundamental aspect of forensic investigations and the implementation of justice. Therefore, the careful selection and application of these techniques, guided by both technological advancement and legal requirements, are crucial for furthering the field of forensic odontology.[28,29]

The London Atlas of Tooth Development and Eruption is a widely recognized reference for estimating age based on dental development. It employs a comparative approach by aligning an individual's dental development and eruption stages with standardized benchmarks outlined in the Atlas, where each stage corresponds to a specific age range established through comprehensive research on tooth growth and eruption timelines.[22,23,25] The reliability of the London Atlas has been consistently demonstrated across various populations, particularly in children and adolescents. For instance, studies in a Nepalese cohort confirmed its high accuracy for age estimation up to 18 years, with exceptional performance in the 16- to 18-year age group,[30] while research in Turkish children found it more accurate than Haavikko's method and Cameriere's European formula.[24] Similarly, its application to a Portuguese population showed effectiveness up to 14 years, although accuracy diminished in older individuals, likely due to genetic polymorphisms influencing dental development beyond early adolescence. These findings underscore the need for population-specific adjustments or complementary methods when using the Atlas for age estimation in older age groups.[31]

The integration of AI into dental age estimation represents a significant advancement in forensic odontology by leveraging deep learning techniques such as CNNs to enhance precision, efficiency, and objectivity.[15] For example, a Malaysian study utilized a hybrid CNN and K-nearest neighbors model to estimate ages from 1,922 panoramic images of individuals aged 15 to 23. The hybrid model achieved exceptional accuracy rates - 99.98% for a 1-year range, 99.96% for a 6-month range, 99.87% for a 3-month range, and 98.78% for a 1-month range - demonstrating its robustness even within narrow age intervals.[32] In a Croatian study, researchers applied the VGG16 deep learning model to analyze 4,035 panoramic radiographs from patients aged 19 to 85, divided into 4 age groups, achieving an overall accuracy of 73% even when applied to archaeological skulls.[14] Similarly, a Korean study focused on dental panoramic X-rays from 1,586 patients, isolating the first molar for age estimation across 3 age categories: 0-19, 20-49, and 50 years and older. This approach yielded accuracy rates between 89.05% and 90.27%. The Korean study also employed advanced visualization techniques, such as heatmaps and Grad-CAM, to identify the specific image regions influencing predictions.[33]

The present study utilized a CNN algorithm to enhance the AlQahtani method for dental age estimation using panoramic radiographs. The CNN algorithm, highly effective at processing 2-dimensional images, was specifically adapted for analyzing these radiographs. Integrating the CNN with the AlQahtani method significantly improved accuracy, achieving 74%, compared to the 53% accuracy reported in the original study by AlQahtani—which analyzed 528 panoramic radiographs of individuals aged 2 to 23 years and 176 radiographs of neonates.[34] This improvement underscores the potential of combining AI-based image processing with traditional dental age estimation techniques to achieve more reliable and precise results in forensic odontology. Challenges common to deep learning models, such as limited training data, overfitting, and underfitting,[35] were addressed using a dataset of 801 panoramic radiographs from outpatients aged 5 to 15 years at a University Dental Hospital in Surabaya, Indonesia. Initially, the CNN model's accuracy was below 50%, which prompted the use of data augmentation to enhance performance. This process expanded the dataset to 1,298 images by applying rotational transformations of 1°-3° in both clockwise and counterclockwise directions, ultimately resulting in an improved accuracy of 74%. Data augmentation increases dataset variability by generating modified versions of original images, such as rotated, mirrored, cropped, or noisy images, thereby reducing the risk of overfitting and improving model generalization.[36]

A comparative study between the Kvaal method and machine learning for age estimation using panoramic radiographs revealed that the XG Boosting Regressor, a machine learning approach, demonstrated superior accuracy with a mean absolute error of 4.77 compared to 5.68 for the Kvaal method.[37] The advantage of machine learning approaches, particularly deep neural networks, lies in their ability to detect a broader range and greater number of features or patterns within panoramic images than is possible through human interpretation. However, interpreting the results of age estimation models remains challenging, as the specific image regions that deep neural networks focus on to identify relevant features are not always apparent. Continued advancements in this field could lead to more accurate and efficient age estimation methods while offering deeper insights into the mechanisms underlying deep neural network analyses.[27]

This study has several limitations that must be addressed to enhance the applicability and reliability of AI-based dental age estimation models. A key limitation is the model's dependence on data augmentation, which was essential for improving the CNN model's accuracy from below 50% to 74%. This reliance suggests that the model may struggle when applied to smaller or less diverse datasets, potentially limiting its generalizability without additional augmentation techniques. Moreover, the variability in accuracy reported across studies - ranging from 73% to over 99% - raises concerns about the reproducibility and reliability of these models across different populations and settings. These challenges underscore the need for further validation and optimization to ensure the robustness of AI-based methods in forensic odontology. Despite these limitations, integrating AI into dental age estimation offers significant potential to enhance accuracy, efficiency, and objectivity by minimizing human error and improving reliability. As AI technology continues to evolve, its role in forensic odontology and other fields requiring precise dental age estimation is expected to grow, paving the way for more consistent and dependable applications.

The integration of AI significantly improves the precision and efficiency of age estimation, providing more reliable and objective results than traditional methods. The London Atlas of Tooth Development and Eruption remains a foundational tool for age estimation, particularly in younger populations; however, its accuracy diminishes in older age groups due to increased variability in tooth development patterns. In this study, the combination of CNNs with the AlQahtani method achieved an accuracy of 74%, highlighting the potential of AI to enhance traditional dental age estimation techniques. Continued advancements in AI are expected to further refine the precision and broaden the applicability of dental age estimation, particularly in forensic settings.

Conflicts of Interest: None

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