

A review of manual, semi-automatic, and automated methods in dental radiographic analysis for clinical and forensic diagnosis

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ABSTRACT

Dental radiography serves as a crucial tool in clinical diagnosis, treatment planning, and forensic identification. Advances in imaging technologies such as panoramic radiography orthopantomogram (OPG), periapical imaging, and cone-beam computed tomography (CBCT) have significantly enhanced diagnostic capabilities. In artificial intelligence (AI) and deep learning (DL) methods have transformed dental image analysis, enabling automated feature extraction, segmentation, classification, and quality assessment with promising clinical reliability. This review systematically synthesizes studies published between 2020 and 2025 across Google Scholar, PubMed, ScienceDirect, Web of Science, and IEEE Xplore. The literature is categorized into six themes: i) imaging modalities and clinical applications, ii) morphometric and forensic analyses, iii) dental age estimation, iv) anatomical landmark detection, v) AI-based diagnostic systems, and vi) image quality evaluation. Findings reveal that convolutional neural networks (CNNs), transformer-based architectures, and hybrid models have achieved high diagnostic accuracy, often surpassing manual assessments. However, challenges remain regarding dataset diversity, acquisition variability, and cross-population generalizability. Addressing these limitations requires the development of standardized, multi-center datasets and domain-adaptive learning frameworks to improve robustness and clinical translation. Overall, this review highlights current progress and research gaps in AI dental radiographic analysis and emphasizes the importance of integrating data standardization and domain adaptation within intelligent dental imaging.

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1. INTRODUCTION

Dental radiography is one of the most widely used imaging modalities in both dental practice and forensic research. It plays a crucial role in diagnosing dental and maxillofacial diseases, guiding treatment planning, and performing morphometric analyses that support forensic identification. Various radiographic techniques including panoramic radiography orthopantomogram (OPG), periapical radiography, cephalometry, cone-beam computed tomography (CBCT), and computed tomography (CT) have long served as standard tools

for evaluating dental and maxillofacial anatomy. However, diagnostic quality is strongly influenced by technical factors such as patient positioning, operator skill, and acquisition protocols. Technical errors may produce artifacts and anatomical distortions, thereby reducing the reliability of clinical interpretation [1]–[3]. This presents a major challenge, as conventional radiographic interpretation relies heavily on clinician expertise and remains prone to subjectivity.

With the advancement of technology, machine learning (ML) and deep learning (DL) methods are increasingly applied in dental radiographic analysis [4]–[6]. Artificial intelligence (AI) has been utilized for various purposes, including image quality enhancement (super-resolution and denoising), anatomical segmentation, object detection, dental condition classification, and age or sex estimation [7]. These developments signify a paradigm shift from subjective manual interpretation toward faster, more objective, and standardized analysis. However, reported performance cannot be interpreted solely on the basis of accuracy, because studies differ substantially in dataset size, population characteristics, annotation procedures, imaging conditions, evaluation metrics, and validation strategies. Consequently, high performance reported under controlled experimental conditions does not necessarily indicate clinical or forensic reliability across diverse populations and imaging settings.

Nevertheless, several methodological and translational gaps remain in the application of AI to dental radiographic analysis. First, the reliability of radiographic analysis remains affected by technical artifacts, acquisition variability, and operator-dependent factors, which may influence both manual interpretation and the quality of data used for AI development. Second, many computer-assisted approaches remain semi-automated and require human intervention, limiting the degree of automation and introducing potential operator-dependent variability. Third, although AI has been increasingly investigated in forensic odontology, robust automated systems for age estimation, sex determination, and human identification remain dependent on the characteristics of the populations and radiographic datasets used for model development and evaluation. Fourth, the availability and representativeness of radiographic datasets remain important constraints, particularly with respect to dataset size, population diversity, image quality, and annotation quality. Importantly, high performance reported on a particular dataset does not necessarily demonstrate generalizability to other populations, institutions, imaging devices, or acquisition conditions. Limited external and cross-population validation therefore remains a critical barrier to establishing the clinical and forensic reliability of AI-based systems. In addition, differences in evaluation metrics and experimental protocols across studies make direct comparison of reported performance difficult.

Although numerous studies have investigated dental radiography for clinical diagnosis, morphometric evaluation, and forensic applications, existing reviews have frequently focused on specific imaging modalities, individual clinical applications, or particular AI techniques. Such reviews provide important information on technological developments but offer limited integration of the different levels of radiographic analysis and automation across clinical and forensic contexts. In particular, a unified comparison of manual, semi-automated, and AI-based approaches, together with consideration of their methodological limitations, reported performance, and applicability across populations and imaging conditions, remains limited. A broader synthesis is therefore needed to distinguish technological progress demonstrated under controlled experimental settings from evidence supporting reliable clinical or forensic application.

Therefore, this systematic literature review aims not only to map recent research trends but also to critically synthesize the methodological development and limitations of dental radiographic analysis. The review provides a unified framework for comparing manual, semi-automated, and AI-based approaches across clinical diagnosis, morphometric analysis, and forensic identification. Particular attention is given to the factors that influence the interpretation of reported performance, including radiographic modality, degree of automation, dataset characteristics, annotation dependency, population diversity, validation strategy, and evaluation metrics. By integrating these dimensions, the review seeks to clarify where AI-based methods demonstrate consistent experimental advantages, where their performance remains dependent on specific datasets or populations, and which methodological barriers currently limit translation into reliable clinical and forensic applications. This framework also enables the identification of research priorities beyond algorithmic development alone, particularly the need for standardized datasets, rigorous external validation, transparent evaluation, and appropriate human-AI collaboration.

This critical synthesis is relevant to the development of intelligent dental radiography systems because it identifies both the potential benefits and the conditions required for reliable implementation. AI-based approaches may reduce operator-dependent variability, accelerate image analysis, and support more consistent interpretation; however, these potential benefits should be distinguished from clinically validated effectiveness. In forensic applications, AI may support age estimation, sex determination, and human identification, but practical use requires appropriate population-specific evaluation, external validation, reproducible procedures, and expert oversight. Accordingly, the findings of this review are intended to provide a basis for assessing the translational readiness of dental radiography AI rather than assuming that reported experimental performance is equivalent to clinical or forensic validity. Specifically, this systematic literature review aims to:

- Summarize recent developments in dental radiography analysis across clinical, morphometric, and forensic applications, including the integration of AI.
- Identify and critically assess the strengths, limitations, and methodological challenges associated with major radiographic modalities, including panoramic radiography, cephalometry, and CBCT.
- Critically evaluate the reported performance and methodological characteristics of ML and DL techniques for image enhancement, segmentation, anatomical landmark detection, clinical diagnosis, and forensic identification, with particular attention to dataset characteristics, population diversity, annotation quality, validation strategies, and the distinction between experimental performance and clinical or forensic applicability.

2. METHOD

This study was conducted as a systematic literature review with narrative synthesis to summarize and critically assess recent developments in dental radiographic analysis across clinical, morphometric, and forensic applications. The review considered conventional and computational approaches involving OPG/PR, CBCT, CT, cephalometry, and other digital dental radiographs. The reviewed applications included age estimation, sex estimation, forensic identification, anatomical landmark detection, structural segmentation, image enhancement, and clinical diagnosis.

The review was structured and reported using the preferred reporting items for systematic reviews and meta-analyses (PRISMA) 2020 framework. The PRISMA-based study-selection process comprised identification, screening, eligibility assessment, and inclusion stages. The review was designed to provide a comparative synthesis of manual, semi-automated, and automated approaches rather than to estimate a pooled diagnostic effect across studies. This distinction was necessary because the included studies differed in imaging modality, target task, dataset characteristics, AI architecture, evaluation metrics, and validation procedures.

A systematic literature search was conducted using five databases: Google Scholar, PubMed, ScienceDirect, Web of Science, and IEEE Xplore. The search covered publications from 2020 to 2025. The databases were selected to capture literature from dental and biomedical research as well as computer science and AI research.

The search strategy used combinations of keywords related to dental radiography, forensic applications, image analysis, and AI. The general search terms included mandible, OPG, CBCT, forensic odontology, age estimation, sex estimation, landmark detection, DL, convolutional neural network (CNN), segmentation, and radiographic. Additional searches were performed using application-specific combinations, including panoramic radiography image quality, panoramic radiograph quality evaluation, osteoporosis detection with DL, osteoporosis classification with ML, detection of dental infection in X-ray radiographs, identification of dental age in radiographs, estimation of dental age in radiographs, identification of gender and age in panoramic radiographs, improving the quality of X-ray radiographs, detection of dental fractures in radiographs, landmark detection in X-ray radiographs, tooth segmentation in X-ray radiographs, tooth classification in panoramic radiographs, numbering and segmentation of teeth in X-ray radiographs, segmentation of mandible in X-ray radiographs, diagnosis of cysts and tumors in panoramic radiographs, and segmentation of cysts and tumors in panoramic radiographs.

The search strategy was designed to capture studies representing different analytical tasks rather than restricting the search to a single AI architecture or radiographic modality. Because the review covered both clinical and forensic applications, multiple keyword combinations were required to identify studies addressing diagnosis, morphometric analysis, image processing, and forensic estimation or identification.

Studies were considered eligible when they met the predefined inclusion criteria. Eligible publications were primary research articles reporting experimental, cohort, case-control, or technical investigations involving dental radiographic images. The studies had to address at least one of the following applications: age estimation, sex estimation, forensic identification, morphometric analysis, anatomical landmark detection, image segmentation, image enhancement, or clinical classification/diagnosis.

Studies were excluded when they were editorials, opinion papers, or single case reports without comparative or analytical methods. Studies that did not directly address dental radiographic analysis within the scope of the review were also excluded during the screening process. The eligibility criteria were applied sequentially during title and abstract screening and subsequent full-text assessment. Potentially relevant records identified during the initial search were retained for further assessment when their eligibility could not be determined from the title and abstract alone. Full-text records were subsequently assessed against the predefined inclusion and exclusion criteria before final inclusion.

The study-selection process is presented in Figure 1 using the PRISMA 2020 flow-diagram structure. A total of 300 records were initially identified across the five databases. After removal of 78 duplicate records, 222 records remained for title and abstract screening. At the screening stage, 128 records were excluded

because they did not meet the scope and eligibility requirements of the review. The remaining 94 reports were assessed for eligibility through full-text evaluation. Following this assessment, 94 studies were included in the final review. Thus, the final evidence base comprised 94 included studies. The selection process was performed according to the predefined eligibility criteria to maintain consistency between the search, screening, and final inclusion stages.

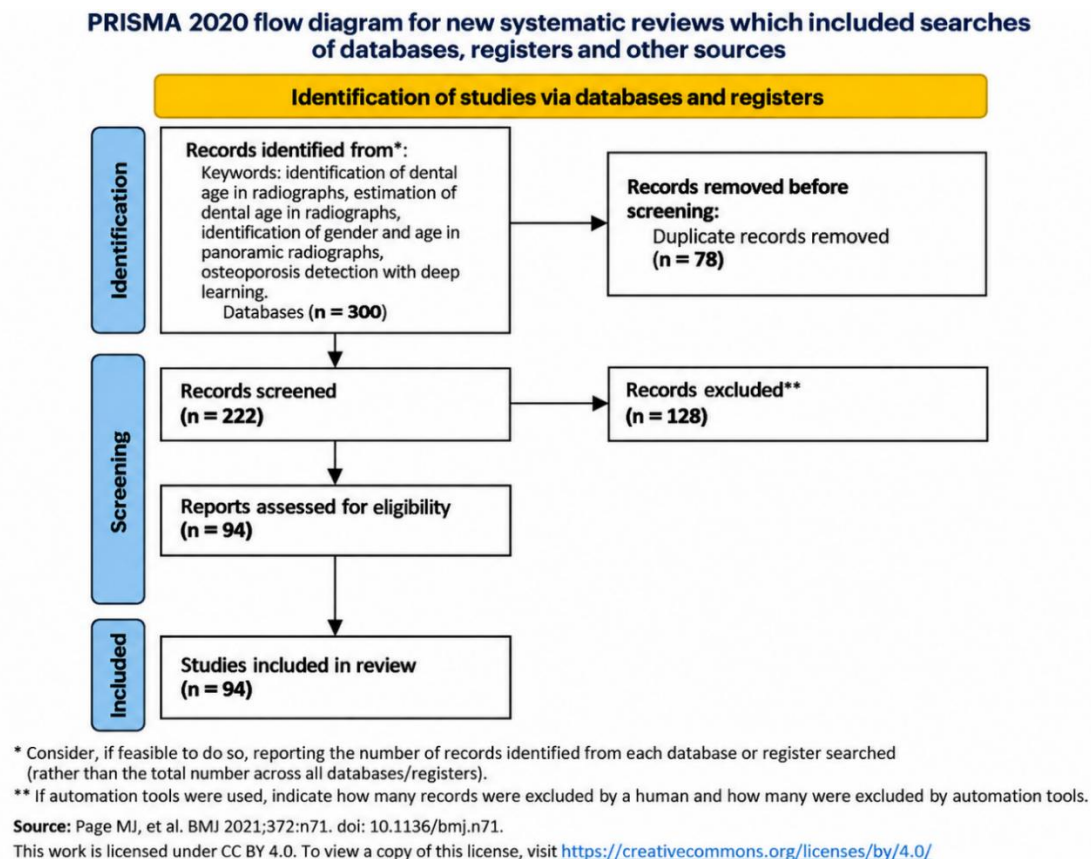


Figure 1. Literature review flowchart

For each included study, information relevant to the objectives of the review was extracted and organized for comparative synthesis. The extracted information included the publication year, radiographic modality, application domain, analytical task, study population or dataset characteristics where reported, analytical approach, AI technique or architecture where applicable, degree of automation, and reported evaluation measures and performance.

Particular attention was given to methodological characteristics that may influence the interpretation of reported performance, including dataset size, population characteristics, image quality or acquisition conditions, annotation requirements, validation strategy, and the evaluation metrics used by each study. These characteristics were considered when comparing findings across studies because reported performance values obtained using different datasets, populations, imaging modalities, target tasks, and evaluation procedures cannot necessarily be interpreted as directly equivalent.

The extracted evidence was synthesized narratively. Quantitative pooling or meta-analysis was not performed because the included studies differed substantially in their imaging modalities, analytical objectives, datasets, AI architectures, evaluation metrics, and experimental designs. Accordingly, reported accuracy and other performance measures were presented as study-specific findings and were not treated as directly comparable estimates of general diagnostic performance. For comparative analysis, the included studies were classified according to the degree of automation involved in the principal radiographic analysis task. Three categories were used: manual, semi-automated, and automated.

Manual analysis was defined as radiographic interpretation or measurement performed by experts without computational assistance for the principal analytical task. Semi-automated analysis was defined as an approach in which software or computational tools assisted specific stages of image analysis but human

intervention remained necessary for the principal analytical workflow, such as manual initialization, selection, correction, or interpretation.

Automated analysis was defined as an approach in which the principal image-analysis task during model inference was performed algorithmically without routine manual intervention. This category included ML and DL methods used for anatomical landmark detection, segmentation, object detection, image enhancement, and classification or estimation tasks. Examples included CNNs, U-Net-based segmentation, You Only Look Once (YOLO) and Faster R-CNN object detection, generative adversarial networks (GANs), super-resolution methods, and AI-based age, sex, or pathology classification.

When a study combined computational analysis with mandatory human intervention or manual correction as part of the principal analytical task, it was classified as semi-automated rather than fully automated. This classification was intended to distinguish the degree of human involvement in the analytical process rather than to imply that an entire clinical or forensic workflow was completely autonomous.

The AI-based studies were further examined according to their principal analytical function, including image enhancement, segmentation, object detection, anatomical landmark detection, classification, age estimation, sex estimation, and forensic identification. The reviewed architectures included conventional ML approaches as well as DL models such as CNNs, U-Net, YOLO, Faster R-CNN, GANs, and transformer-based approaches where reported in the included studies.

The reported performance of AI-based methods was examined together with the characteristics of the datasets and validation procedures used in each study. Accuracy, sensitivity, specificity, precision, F1-score, mean absolute error, and other metrics were considered according to the measures reported by individual studies. Because these measures were not consistently reported across all studies and were often calculated under different experimental conditions, no single performance metric was used as a universal criterion for ranking all reviewed methods.

Particular attention was given to whether studies evaluated their models using independent, external, or cross-population datasets when such information was reported. This allowed the review to distinguish between performance demonstrated within the development dataset or a closely related test set and evidence supporting generalization to different populations or imaging conditions.

The reviewed studies were analyzed across three principal application domains: clinical diagnosis, morphometric analysis, and forensic identification. Clinical applications included the detection or classification of dental and maxillofacial conditions and related radiographic abnormalities. Morphometric applications included anatomical measurement, landmark localization, segmentation, and image-based structural analysis. Forensic applications included age estimation, sex estimation, and human identification.

The comparative synthesis considered the relationship between the analytical approach, degree of automation, radiographic modality, and reported performance. For forensic applications, additional attention was given to population characteristics and validation procedures because performance obtained from a specific population may not necessarily be transferable to other populations. The review therefore considered population dependence and external validation as methodological factors when assessing the reported applicability of AI-based forensic systems.

Finally, the included studies were examined to identify recurring methodological limitations affecting the interpretation and potential application of dental radiography AI. These included limited dataset size, restricted population diversity, variability in image quality and acquisition conditions, dependence on manual annotation or correction, differences in evaluation metrics, and limited external or cross-population validation where reported.

The synthesis was used to identify research priorities for the development of more reliable dental radiography analysis systems. These priorities were considered in relation to methodological reproducibility, dataset standardization, validation across independent populations and imaging conditions, interpretability of AI predictions, and the integration of AI-assisted analysis into clinical and forensic workflows.

3. DISCUSSION

3.1. Manual approaches to dental analysis

Panoramic and periapical radiographs are widely used to identify dental anomalies, including multiple phenotypic patterns of tooth agenesis, most commonly affecting the maxillary lateral incisors and mandibular second premolars. A high prevalence of dento-osseous anomalies has also been reported in patients with *familial adenomatous polyposis* [8]. Panoramic radiography remains the preferred method for assessing impacted mandibular third molars in relation to the inferior alveolar canal, offering improved diagnostic accuracy [9]. Furthermore, CBCT-based maxillary sinus measurements have proven to be reliable for sex determination and human identification [10]. Radiographic techniques also play a key role in age estimation. Strong correlations between dental and chronological age have been demonstrated in Bosnian populations [11].

Age-related changes, such as increased tooth loss, endodontic treatments, and positional shifts of the mandibular canal and mental foramen, further highlight the diagnostic value of panoramic imaging [12]. In addition, panoramic and CBCT-based analyses have been applied to assess bruxism-induced trabecular bone alterations influenced by laterality and sex [13], underscoring their importance not only in dental diagnostics but also in forensic and systemic investigations.

Overall, these findings demonstrate that conventional radiographic measurements can provide useful anatomical and morphometric information for clinical and forensic assessment. However, the reported reliability is closely associated with the specific anatomical parameters, imaging modality, and population examined. Therefore, the reported performance of manual measurements should not be interpreted as universally transferable across populations or imaging conditions.

3.2. Semi-automated approaches to dental analysis

Semi-automated methods utilize software tools such as ImageJ or radiology-specific applications to improve measurement objectivity, for instance, by assessing cortical thickness (CTh) and fractal dimension (FD) in patients with cemento-osseous dysplasia (COD) [14]. These methods enhance measurement consistency compared with manual evaluation, although operator input is still required [15]–[17]. Thus, semi-automated approaches represent an intermediate level of automation: they can reduce variability in specific measurement steps while retaining expert involvement for initialization, correction, or interpretation. Their reported advantages therefore reflect improved assistance rather than complete replacement of human assessment.

3.3. Automated analysis in dentistry

Recent research has increasingly focused on automating diagnosis using DL models such as CNN, densely connected convolutional networks (DenseNet), residual network (ResNet), Visual Geometry Group (VGG), YOLO, and Mask R-CNN. These methods have been applied to various tasks, including mandibular fracture detection [18]; tooth segmentation [19]; automatic age estimation [20]; classification of maxillary canine impaction [21]; and implant brand and angulation identification [22]. Additional applications include the detection of radiolucent lesions, cysts, tumors, and other dental abnormalities (Figure 2) [23], implant detection [24], periodontitis recognition [25], identification of ectopic teeth [26], restoration detection [27], and assessment of other dental conditions [28].

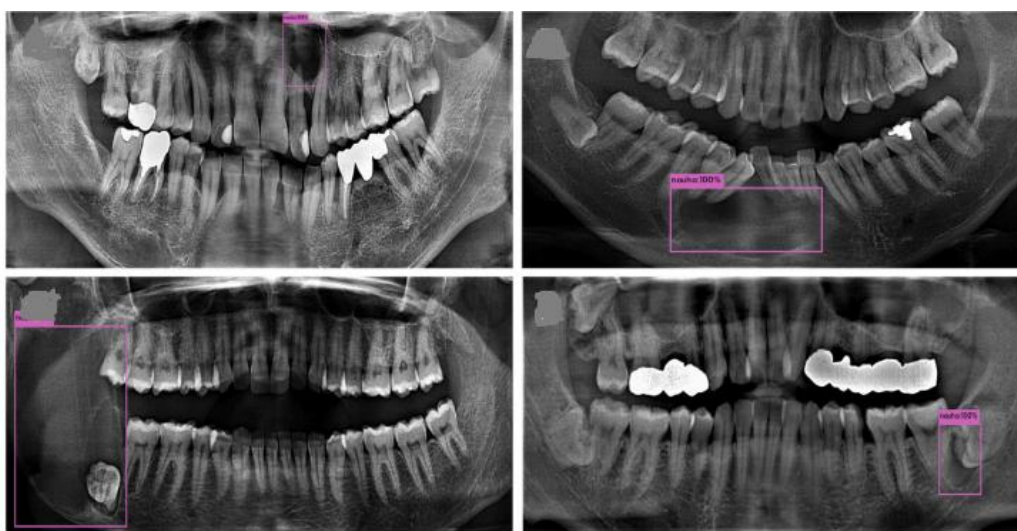


Figure 2. Research findings on lesion detection using DL [23]

DL models have demonstrated strong performance in lesion detection (Figure 3) [29]. Reported accuracies vary widely (approximately 70%-99%), depending on dataset size, imaging modality, and task complexity. Some studies report reduced performance in small or imbalanced datasets. These findings indicate that AI-based approaches can achieve promising performance for specific radiographic detection tasks under the conditions evaluated in individual studies. However, such experimental performance should not be equated with clinically validated effectiveness, particularly when models are developed and evaluated using limited or population-specific datasets.

3.4. Manual analysis for forensic identification

Early forensic research relied heavily on manual evaluation, with cranial parameters such as biauricular breadth and skull weight proving to be highly dimorphic and useful for sex estimation in the South Indian population. Panoramic radiographs have since demonstrated strong forensic value, as radiomorphometric indices like mandibular cortical index (MCI), mandibular cortical width (MCW), panoramic mandibular index (PMI), alveolar bone loss (ABL), height at first premolar (Hp), and height at first molar (Hm) effectively assess ABL influenced by sex and age [30]. Including studies on Portuguese populations confirming the predictive power of morphometric traits for identification [31]. CT-based studies further revealed that while the cranium provides higher reliability for sex estimation, mandibular accuracy improves with age [32].

Mandibular measurements from CBCT and panoramic radiographs consistently confirm sexual dimorphism, with bicondylar breadth, mandibular base length, and ramus height serving as reliable sex predictors, and gonial angle as a supporting feature [33], [34]. Age estimation methods, such as the Tooth Coronal Index and mandibular morphometry, show strong correlation with chronological age, achieving accuracies up to 90% in certain populations [35]. Additional findings on chin morphology greater width in males and greater height in females further reinforce mandibular metrics as robust indicators for sex and age estimation in forensic applications [36].

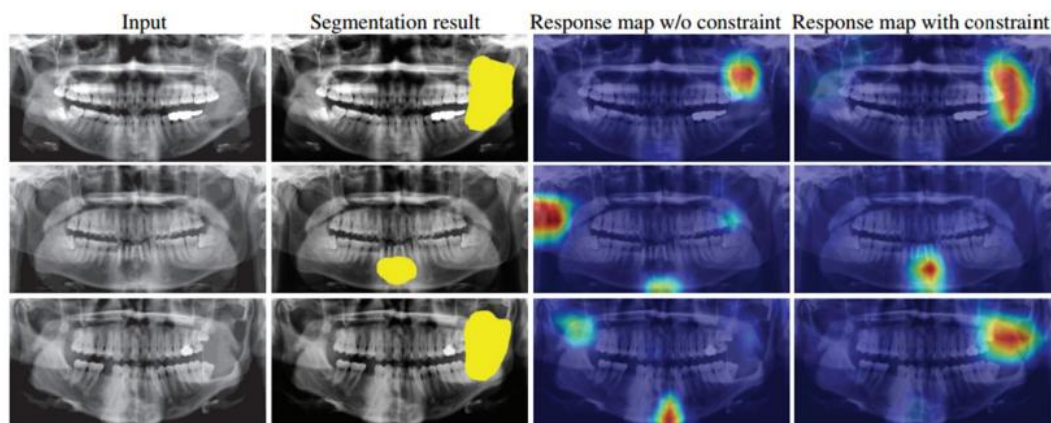


Figure 3. Lesion segmentation results from DL [29]

3.5. Semi-automated analysis for forensic identification

Mandibular parameters and dental radiographs have shown strong potential in forensic identification, serving as reliable biometric markers. Morphological and morphometric analyses reveal clear sexual dimorphism in the mandible, with bigonial breadth, condylar and coronoid height, and ramus breadth identified as key predictors of sex [37]. Ramus length also correlates strongly with age [38], making it useful for age estimation [39]. CBCT-based studies further confirm these dimorphic traits across populations and establish population-specific reference standards [40]. Recent advances in automation and ML have strengthened forensic applications. Artificial neural networks (ANNs) outperform manual methods in sex classification [41], while models based on mandibular landmarks in panoramic radiographs provide reliable sex estimation [42]. Automated systems now enable accurate radiograph matching for personal identification [43] and enhance segmentation of jaw and tooth structures [44], reinforcing the mandible's value as a robust forensic biomarker.

3.6. Automated analysis in forensic identification

Recent studies demonstrate substantial development in the application of DL to forensic dental radiography. The dual-path CNN model (DASNet), which integrates age and sex prediction, was reported to outperform DANet by incorporating sex-related features into age estimation [45]. Panoramic tooth-mask models achieved rank-1 and rank-10 identification accuracies of 88.62% and 96.16%, respectively [46]. CNN-based systems have also been investigated for human identification in mass-disaster and criminal-investigation contexts without requiring specialized equipment [47]. Multi-task learning approaches have reported accuracies above 99% for sex and age estimation, while studies using larger datasets have reported CNN-based classification accuracies exceeding 95% [48]. Other studies reported per-tooth accuracies of approximately 89%-90%, with AUC values of 0.94-0.98, highlighting the potential relevance of pulp and alveolar-bone

characteristics for age estimation [49]. Automated matching of ante-mortem and post-mortem panoramic radiographs has also reported accuracies of up to 100% in specific cases, whereas other approaches achieved performance in the range of 80%-95% [50], [51].

Despite these promising results, the reported performance is heterogeneous and should be interpreted within the specific datasets, populations, imaging conditions, target tasks, and evaluation procedures used in each study. High accuracy obtained from a particular dataset does not by itself establish that an AI system is reliable across different populations or forensic case conditions. This issue is particularly relevant to age and sex estimation because population-specific anatomical and demographic characteristics may influence model performance. Similarly, the performance of radiograph-matching systems may depend on image quality, acquisition conditions, and the availability of sufficiently distinctive dental structures. Therefore, the current evidence supports the experimental feasibility of automated forensic dental analysis, but does not establish universal forensic validity or routine forensic applicability.

From a practical perspective, automated systems may reduce the time required for radiographic analysis and provide decision-support for forensic experts, particularly in applications such as age estimation, sex estimation, and ante-mortem/post-mortem identification. However, implementation requires standardized datasets, evaluation using independently collected populations, transparent validation procedures, and appropriate expert oversight. The absence of standardized benchmark datasets and the limited diversity of some existing datasets remain important barriers to determining whether reported performance can be reproduced under different forensic conditions. Thus, future development should emphasize robust external and cross-population validation alongside algorithmic improvement rather than relying solely on increasingly complex architectures.

3.7. Manual landmark analysis on radiographs

Manual analysis remains an important reference approach in radiographic landmark assessment, particularly for evaluating the reproducibility of mandibular landmarks in forensic applications [52]. CBCT has also been used to determine the midsagittal plane in both symmetric and asymmetric facial structures. These studies demonstrate the continued relevance of expert-based landmark identification; however, manual landmark placement remains susceptible to observer-dependent variability. Consequently, manual analysis provides an important reference for evaluating automated landmark-detection methods, but its reproducibility depends on the observer and the specific anatomical landmarks being assessed.

3.8. Semi-automated landmark analysis on radiographs

Semi-automatic methods have been developed to reduce the subjectivity inherent in manual analysis. In lateral cephalometric studies, plane-based segmentation demonstrated greater consistency than point-based approaches for assessing mandibular growth direction [53]. A combined manual-semi-automatic system applied to CBCT enabled accurate evaluation of midsagittal landmarks with minimal deviation in symmetric faces. Although such methods improve consistency, manual validation remains necessary to ensure accuracy.

3.9. Automated landmark analysis on radiographs

Most recent studies have developed fully automated systems for landmark detection in dental radiography. In 3D CBCT, ML approaches detect landmarks with errors of approximately 1-2 mm, while multi-stage CNNs achieve around 1.03 mm [54], [55]. In cephalometric analysis, models such as CephaNet (Faster R-CNN) and other CNN-based frameworks reduce detection error and improve efficiency [56], [57]. DL methods applied to mandibular CBCT report errors as low as 0.21 mm and achieve 87.8% accuracy in age estimation [58]. For panoramic radiographs, YOLOv5 achieves sensitivity above 0.9, while AI-assisted asymmetry detection reports errors below 1 mm [59], [60]. Advanced models such as SkullEngine and pix2pixGAN further support applications including surgical planning and synthetic cephalogram generation [61], [62].

Despite these promising results, performance varies depending on imaging modality, dataset size, and landmark complexity. These methods offer significant potential for improving efficiency and consistency in clinical diagnosis and orthodontic planning. However, most models are trained on limited datasets and may lack generalizability across diverse populations and imaging conditions, which remains a key challenge for real-world implementation. However, the reported localization errors cannot be interpreted as directly equivalent measures of performance because landmark definitions, imaging modalities, anatomical complexity, datasets, and evaluation procedures differ among studies.

3.10. Manual quality analysis of radiographs

The majority of studies have evaluated patient positioning errors and radiographic quality through manual assessment. Common errors include failure of the tongue to contact the palate, head rotation, and incorrect chin positioning. Early investigations demonstrated that these errors remain frequent and negatively affect diagnostic quality [63]. Positioning errors are strongly associated with dentition type (mixed, primary,

or edentulous) and the operator's level of training. Several studies have reported that more than 80% of radiographs contain at least one error [64]. In cases involving mandibular fractures, error rates were even higher due to the limited mobility of patients [65]. Research on pediatric radiographs revealed that 43.6% contained positioning errors, most frequently the tongue not being pressed against the palate [66]. Overall, manual evaluations consistently highlight the high prevalence of patient positioning errors, underscoring the need for standardized procedures and improved operator training [67], [68].

3.11. Semi-automated quality analysis of radiographs

Phantom studies using line-pair and ball-type phantoms have been conducted to evaluate the correlation between spatial resolution and ball distortion rate. The findings revealed that distortion increased toward the peripheral regions of the image, with a 20% ball distortion rate proposed as the threshold for maintaining diagnostic quality [69]. Further image analyses based on objective parameters such as cross-correlation, peak signal-to-noise ratio (PSNR), and deformable image registration have clarified the impact of patient rotation and translation errors. Specifically, chin rotation greater than 6° produced significant distortion, while PSNR values above 30 dB were achieved only under minimal translational error [70].

3.12. Automatic analysis of radiograph quality

DL approaches have improved radiographic quality assessment. GANs enhance low-resolution images by reducing noise and artifacts, while multi-scale CNNs enable automated quality evaluation with higher performance than conventional methods [71]. A hybrid approach combining six CNNs with six support vector machines (SVMs) detects patient positioning errors with an accuracy of 83.2% [72]. These approaches can improve image-quality metrics and visual characteristics under the evaluated conditions; however, improvement in image-quality metrics does not necessarily demonstrate improved diagnostic accuracy or clinical decision-making. Collectively, these AI-based approaches support more efficient and objective quality control in clinical workflows, particularly in reducing operator-dependent errors. Nevertheless, most models rely on limited datasets and may not generalize well across different imaging conditions and patient populations [73].

3.13. Automatic enhancement of radiograph quality

Automatic methods enhance the resolution and overall quality of dental radiographs. Super-resolution CNNs generate sharper images without increasing radiation dose, while the MSTHGR method improves contrast, detail, and edge clarity with higher contrast improvement ratio (CIR), entropy, and spatial frequency (SF) values. GANs, including DCGAN and WGAN-GP, also generate realistic synthetic images to address the limitation of small datasets. Variants such as SRCNN, SRGAN, and autoencoders achieve structural similarity index (SSIM) values of 0.82-0.98 and PSNR values up to 40.2. Reported performance varies depending on dataset characteristics and imaging conditions. These approaches improve diagnostic visibility in dental radiographs; however, their effectiveness remains dependent on dataset size, acquisition protocols, and model generalizability [74].

3.14. Automated segmentation analysis of radiographs

Many studies have focused on developing automatic segmentation methods for dental radiographs. In periapical X-rays, multi-task CNNs improve classification accuracy [75]. While transfer learning-based CNNs enable effective segmentation of teeth and mandibular structures in panoramic radiographs [76]. In CBCT and CT imaging, approaches such as region merging and coarse-to-fine 3D SegUnet have been applied [77]. Recent methods include Mask R-CNN, CBTrans, SASeg, and RCNNSeg [78]–[81]. These approaches have demonstrated improved segmentation performance in the evaluated datasets and may facilitate downstream applications such as diagnosis and treatment planning. However, the clinical benefit of improved segmentation performance requires separate validation in the corresponding clinical workflow.

3.15. Automated detection and numbering analysis on dental radiographs

Automated detection and numbering of teeth have been investigated using object-detection and DL approaches to reduce the time and manual effort required for radiographic assessment. YOLOv4 achieved an accuracy of 88.5% for tooth detection and numbering [82]. Other approaches combining DL models with detection or classification strategies reported precision values of up to 99.9% [83]. Other methods integrating U-Net, Faster R-CNN, and VGG16 also reported high precision and recall values [84]. DL models have been applied for mandibular canal detection and computer-assisted diagnostic systems [85], [86]. These results demonstrate that automated methods can achieve high performance for specific tooth detection and numbering tasks. However, the reported values should be interpreted within the specific datasets, tooth classes, imaging conditions, and evaluation procedures used in each study. Direct numerical comparison among studies is

therefore limited because differences in dataset composition, class distribution, annotation procedures, and evaluation metrics may substantially affect the reported performance. In addition, high detection or numbering performance on a particular dataset does not by itself establish robustness across different patient populations or radiographic acquisition conditions. Accordingly, current evidence supports the feasibility of automated tooth detection and numbering, while further independent and cross-population validation is required before such systems can be considered broadly reliable for routine clinical application.

3.16. Automated analysis of dental abnormalities and conditions on radiographs

DL has been increasingly applied to the classification of dental conditions, demonstrating improved diagnostic performance. Reported accuracies range from approximately 70% to over 90%, depending on the task and dataset. For example, AlexNet achieved 70% accuracy in classifying tooth abnormalities [87], while hybrid models reported higher performance for detecting temporomandibular joint osteoarthritis and other conditions [88]. Multitask CNN architectures further improve segmentation and classification performance [89]. DL approaches also enhance implant classification and caries detection [90], [91]. The availability of public datasets, such as the Tufts Dental Database, supports model development and benchmarking [92]. Despite these advances, performance varies across datasets and conditions, and many models are trained on limited or population-specific data. This may introduce bias and limit generalizability in real-world clinical applications. Consequently, the reported accuracy range should be interpreted as study-specific performance rather than a general estimate of AI diagnostic accuracy in dental radiography.

3.17. Osteoporosis analysis on radiographs

Bone mineral density (BMD) T-scores have been reported to correlate significantly with age, MCI, MCW, PMI, and sex; individuals with Class 3 MCI, MCW <3 mm, and PMI <0.3 were reported to have a higher risk of osteoporosis [93]. Texture and bone-edge analyses using Gabor algorithms also demonstrated promising diagnostic performance, supporting the potential of dental radiographs for osteoporosis risk assessment [94]. These findings indicate that dental radiographs may provide information relevant to osteoporosis screening; however, the reported associations and diagnostic performance should be interpreted within the populations, imaging conditions, and evaluation procedures examined in the individual studies. In particular, evidence of association or classification performance does not by itself establish that dental radiographs can replace established diagnostic procedures for osteoporosis. Variability in imaging conditions, patient characteristics, and study populations may also affect the reproducibility and generalizability of the reported findings.

A comparative synthesis indicates that manual methods remain important reference approaches but are subject to observer-dependent variability. Semi-automated methods can improve consistency for specific measurement tasks while retaining human intervention. Automated AI-based methods have demonstrated promising performance and can reduce manual processing requirements; however, their reported accuracy and reproducibility remain dependent on the dataset, population, imaging modality, target task, and evaluation procedure. Therefore, the evidence does not support treating automated AI as universally superior to manual or semi-automated approaches. Instead, the reviewed literature indicates a trade-off between automation, human oversight, methodological standardization, and validation requirements. Table 1 summarizes the key differences among manual, semi-automated, and automated approaches.

Table 1. Method comparison

Method	Reported performance	Efficiency	Reproducibility	Main limitations
Manual	Low-high (variable)	Low	Operator-dependent	Subjectivity, observer variability
Semi-automated	Generally improved for specific	Medium	Improved for assisted measurements	Human intervention remains necessary
Automated (AI)	Promising but task- and dataset-dependent	Potentially high	Potentially high under standardized conditions	Dataset bias, limited interpretability, external-validation requirements

4. CONCLUSION

Panoramic radiography remains the primary modality in dental practice due to its efficiency, while CBCT provides the three-dimensional detail required for complex diagnoses and forensic applications. Manual evaluation is still relevant as the reference standard, although it is limited by subjectivity and operator-dependent variability. Semi-automated approaches improve measurement consistency, whereas automated methods based on AI have demonstrated very high accuracy, often matching or exceeding expert performance in age estimation, sex determination, individual identification, and even systemic condition detection.

Advances in DL, particularly CNN, U-Net, YOLO, Faster R-CNN, and GAN, have revolutionized dental radiographic analysis. Their applications include image quality enhancement, automated segmentation

of maxillofacial anatomical structures, tooth detection and numbering, and classification of dental and bone conditions. Recent researches show that AI can provide rapid, objective, and efficient analysis with low error rates (<2 mm in landmark detection), highlighting its potential for both clinical and forensic implementation.

Nevertheless, key challenges remain, including limited dataset size and diversity, image artifacts, and difficulties in achieving generalizability across populations. Panoramic radiography is also highly susceptible to technical errors, particularly patient positioning, which can substantially affect diagnostic accuracy. Therefore, multicenter researches with large, diverse datasets that adhere to international standards are essential to develop more robust, adaptive, and widely applicable AI systems.

This review underscores the need to integrate findings across manual, semi-automated, and automated approaches, as well as across radiographic modalities, to establish comprehensive and applicable guidelines for the future development of dental radiography in both clinical and forensic.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no commercial, financial, or personal relationships that could be construed as a potential conflict of interest in relation to the research, authorship, or publication of this article. All authors have reviewed and approved the final version of the manuscript and agree with its submission.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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