© September 2026 | IJIRT | Volume 13 Issue 4 | ISSN: 2349-6002

Real – Time Forensic Age & Sex Estimation Using Ai on Panoramic Radiographs

Dr Pranay Kumar Singh[1], Dr Shradha Sharma[2]
[1,2] *Manav Rachna Dental College, MRIIRS*

Abstract—**Background: Legal medicine, forensic identification, and disaster victim identification (DVI) all depend on accurate estimates of age and sex. Conventional radiographic and morphological techniques take a lot of time and are prone to fluctuation both within and between observers. New developments in artificial intelligence (AI), especially deep convolutional neural networks (CNNs), provide a real-time, automatic, and objective substitute. Because they provide a thorough picture of maxillo-mandibular growth, tooth mineralization, and skeletal architecture, digital panoramic radiographs (also known as orthopantomograms, or OPGs) are a perfect diagnostic modality for AI deployment.**

Objective: Using digitized panoramic radiographs from a wide range of demographics, this study developed, cross-verified, and validated an autonomous, dual-task deep learning framework for the simultaneous, real-time assessment of biological sex and chronological age.

Materials and Methods: 12,500 high-resolution digital OPGs of patients ranging in age from 4.5 to 25.0 years were gathered from multicentric archives to provide a diverse dataset. The dataset was subjected to normalization, anatomical masking, and strict quality screening. An attention-gated ResNet-101 backbone was incorporated into a customized, multi-task deep convolutional neural network architecture that was designed to process single OPG inputs and split into two parallel computational pathways: a binary classification network for sex determination and a regression network for chronological age estimation. A strict double-check validation procedure was put in place to guarantee complete authenticity and exclude algorithmic bias. A 20% hold-out test set and an 80% training/validation set were created from the dataset. An external validation cohort (n = 2,500) from geographically separate universities not included in the training phase was used to do cross-verification. The network's regions of interest were mapped using Grad-CAM (Gradient-weighted Class Activation Mapping) visualizations, which offered forensic accountability and cryptographic explainability for the model's decision-making processes.

RESULTS: Real-time inference speeds of 42 milliseconds per input were attained by the optimized multi-task AI architecture. Over the whole hold-out test set, the model showed an overall Mean Absolute Error (MAE) of ± 0.38 years (95% Confidence Interval [CI]: 0.34–0.42 years) for chronological age prediction. The mixed-dentition sub-cohort showed the highest precision (MAE of ± 0.21 years). The system's overall accuracy for determining biological sex was 94.6% (Area Under the Receiver Operating Characteristic curve [AUC-ROC] = 0.978). With an accuracy of 93.8% for sex categorization and an MAE of ± 0.41 years, external cross-verification verified the stability of the model. Grad-CAM heatmaps confirmed that the network prioritized mandibular ramus flexure and gonial angle morphology for sex categorization while heavily relying on the mineralization condition of mandibular third molars and canine pulp-to-tooth ratios for age progression.

CONCLUSION: This paper presents a highly accurate, authenticated, and cross-verified AI system that can provide real-time simultaneous age and sex estimation from panoramic radiographs. This methodology meets the stringent evidence requirements needed for legal testimony, forensic casework, and international humanitarian DVI operations by offering objective measurements in addition to explainable attention maps.

I. INTRODUCTION

I. At the nexus of human identification, legal medicine, and forensic science, complete objectivity, speed, and precision are required. Determining biological sex and chronological age forms the basis of the forensic profile. This profile is crucial for carrying out disaster victim identification (DVI) procedures, identifying unidentified human remains, and settling civil or criminal problems involving people who do not have proper documentation. Conventional anthropological and odonto-stomatological approaches mostly rely on the subjective, physical assessment of dental and skeletal development. Although frequently used approaches such as Demirjian's or Schour and Massler's are hampered by significant intra- and inter-observer variability, laborious procedures, and population-specific biases. The use of human experts to manually assess and interpret these developmental markers generates crucial bottlenecks that might impede legal procedures and humanitarian actions in a world that moves quickly.

II. For automated forensic evaluation, digital panoramic radiography, also known as orthopantomography (OPG), is the best diagnostic technique. The maxillo-mandibular complex can be seen in both directions in a single OPG. Dental mineralization phases, tooth eruption sequences, pulp-to-tooth ratio decreases, and unique maxillofacial skeletal features are all simultaneously displayed as important indicators. In the past, using these rich morphological characteristics required meticulous examination by qualified experts. However, the development of deep convolutional neural networks (CNNs), a type of artificial intelligence (AI) and enhanced computer vision, offers a revolutionary chance to transform these static radiographs into extremely dependable, quantified forensic assets. AI systems can quickly analyze intricate patterns in OPGs that are frequently invisible to the human eye by automating feature extraction, setting a new benchmark for forensic accuracy.

III. Despite the potential of deep learning architectures, there are still significant gaps in the research with regard to multi-task synthesis, real-time performance, and clinical accountability. The majority of current AI models function as limited, single-task systems that assess sex or age separately. This method repeats the required computational overhead and artificially divides a naturally cohesive diagnostic workflow. Moreover, a lot of models operate as "black boxes." They are susceptible to adversarial errors and inadmissible under strict legal evidentiary standards, such as the Daubert or Frye criteria, because they lack explainable boundaries or obvious validation procedures. This paper presents an autonomous, real-time, dual-task deep learning architecture to address these shortcomings. It delivers actionable intelligence in milliseconds by using an attention-gated ResNet-101 backbone designed to concurrently compute biological sex and chronological age from a single panoramic input.

IV. This study uses a rigorous "double-checked" and cross-verified validation architecture to eliminate data overfitting and ensure unquestionable forensic accountability. A multicentric dataset of 12,500 high-resolution digital OPGs encompassing a wide range of demographics (ages 4.5 to 25.0 years) was used to train and internally validate the model. The methodology underwent rigorous external cross-verification utilizing a completely isolated cohort of 2,500 radiographs from geographically separate institutions to guarantee the integrity of its performance indicators. This external validation ensures that the predicted accuracy of the system is not a result of particular scanner calibrations or localized institutional imaging artifacts. Additionally, the incorporation of Gradient-weighted Class Activation Mapping (Grad-CAM) offers cryptographic explainability by clearly revealing the precise bone and dental anatomical features underlying each mathematical result.

V. This introduction creates an automated forensic identification system that is extremely exact, auditable, and disciplined. This system offers an objective, repeatable approach that reduces human bias by providing real-time estimating speeds combined with a low Mean Absolute Error (MAE) and good classification accuracy. The gap between conclusive forensic evidence and unprocessed radiological data is directly filled by the dual-pathway computational design. The technical setup, mathematical verification, and morphological insights of this AI system are described in depth. In the end, it shows that the framework meets the strict requirements for precision and responsibility needed for contemporary court testimony and global humanitarian efforts.

II. METHODOLOGIES

I. This multi-task framework's fundamental integrity is based on a diverse, multicentric dataset of 12,500 high-resolution digital panoramic radiographs (OPGs). To guarantee demographic, racial, and socioeconomic diversity, the primary cohort was retrospectively mined from institutional picture archiving and communication systems (PACS) at five different tertiary healthcare and dental training facilities. Patients between the ages of 4.50 and 25.00 who had complete maxillofacial structures, verifiable chronological birth records, and standard clinical indications for imaging were eligible for inclusion. Radiographs with severe motion artifacts, major maxillofacial injuries, gross pathological lesions (such as ameloblastomas or expanding cysts), or extensive orthodontic appliances on both sides were categorically rejected. All participating locations obtained Institutional Review Board (IRB) permissions, and before to computational intake, all data were rigorously de-identified in accordance with international health data privacy standards.

II. A deterministic picture preprocessing pipeline was developed to reduce hardware-induced variations resulting from different digital X-ray sensor setups and exposure conditions. In order to maximize computational performance while maintaining important morphological boundaries, raw DICOM images were converted to lossless 16-bit PNG format and downsampled using bilinear interpolation to a standardized spatial resolution of 1024×512 pixels. Using a tile grid size of 8×8 and a clip limit of 2.0, Contrast Limited Adaptive Histogram Equalization (CLAHE) was used to improve modest radiological density gradients in dental pulp cavities, root apices, and trabecular patterns. Min-Max normalization was used to dynamically scale the pixel intensities into a floating-point range of. During the training phase, the Albumentations library was used to augment the training subset with controlled geometric transformations such as specular horizontal flipping, random rotations(± 5) , and mild elastic deformations in order to prevent overfitting and improve structural invariance.

III. An designed, multi-task deep convolutional neural network (CNN) based on a modified ResNet-101 backbone initialized with pre-trained ImageNet weights makes up the fundamental computational architecture. The network was altered by incorporating specialized attention-gating modules into the residual blocks of stages 3 and 4 and eliminating the conventional terminal fully linked classification layer. By dynamically calculating spatial weight vectors, these attention gates highlight high-variance forensic indicators in the maxillo-mandibular complexes while reducing unnecessary anatomical noise (such as nose fossae and cervical spine shadows). The computational pipeline splits into two separate, parallel functional streams—an Age Regression pipeline and a Sex Classification Pathway—after the last attention-gated convolutional layer. The network may simultaneously optimize low- and mid-level structural characteristics within the shared backbone thanks to this parallel design, significantly reducing the overhead associated with dual-model inference.

IV. After a shared 2D Global Average Pooling (GAP) layer compresses the spatial feature maps into a 2048-dimensional vector, the parallel branches split off right away. Rectified Linear Unit (ReLU) activations are used by the Age Regression Pathway to route this feature vector into a dense bottleneck layer with 512 neurons, which is stabilized by a 30% dropout regularizer. A continuous, high-precision numerical number representing chronological age in years is produced when this stream ends in a single-neuron layer with a linear activation function. The shared vector is simultaneously guided through the same dense architecture by the Sex Classification Pathway, which ends in a single-neuron layer with a Sigmoid activation function. This configuration creates a strong framework for binary biological sex classification by computing a deterministic probability distribution that ranges from 0.0 (absolute male assignment) to 1.0 (absolute female assignment).

V. The AI learns both gender classification and age estimation at the same time using a bespoke combined error score. While an optimized learning routine halves the learning pace if performance stalls, an automated coordinator balances these parameters to guarantee that neither task dominates the training process.

VI. The AI's training and testing data were kept entirely apart to guard against cheating and guarantee actual accuracy. The final test employed a completely separate set of 2,500 scans from completely distinct clinics, whereas the initial test included 12,500 scans. This demonstrates that the system is not limited to memorizing pictures from its native hospitals and operates globally.

VII. The architecture was designed with quick, real-time forensic deployment in mind. The NVIDIA TensorRT optimization libraries, which combine redundant layers and transform high-precision floating-point weights into extremely effective FP16 half-precision representations, were used to build and export the trained model weights. An enterprise workstation with an NVIDIA RTX 4090 GPU was used to implement the inference pipeline, which was backed by a C++ automated API wrapperThis production wrapper keeps an eye on incoming OPG uploads in a specific secure location. In order to achieve an operational turnaround time measured in milliseconds per case, it automatically performs the preprocessing steps, feeds the data through the dual-branch network, and outputs a structured forensic report with the estimated age, biological sex, and confidence scores.

VIII. A strong visual auditing framework was incorporated to remove the clinical hazards related to "black-box" AI systems and meet the legal requirements for expert testimony. The final convolutional layers of both functional branches were connected to Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM creates high-resolution spatial saliency heatmaps by dynamically extracting the gradients of the target outputs with respect to the final feature maps for each inference procedure. These heatmaps, which illustrate the precise regions influencing the model's predictions, are superimposed on the original radiograph using a standardized color spectrum. This visual evidence provides clear, auditable accountability for court presentations by enabling forensic experts to confirm that the model's sex determinations are based on stable skeletal markers (such as the mandibular ramus flexure or gonial angle) and its age estimates are based on reliable biological indicators (such as root mineralization or pulp-chamber narrowing).

III. RESULTS

A. Under real-world testing conditions, the multi-task deep neural network optimized by TensorRT demonstrated remarkable and stable computational productivity. The system recorded an average inference speed of 42.1 milliseconds per orthopantomogram (OPG) over 2,500 radiographs in the internal hold-out dataset. Data preparation, dual-branch prediction, forward-pass execution, and automated PDF report production are all included in this timeline. Performance metrics stayed constant at 45.4 milliseconds per image when tested on the external cross-verification dataset (n = 2,500) utilizing various network hardware configurations. This speed shows that the model can provide actionable forensic measures at the point of care quickly, which makes it very useful for high-volume casework at international border crossings and real-time triage during big disasters.

B. The mean error of the age estimation tool was ±0.38 years for the internal test group and ±0.41 years for the fully independent external group. This consistent performance in many testing scenarios validates the model's worldwide dependability for forensic investigations by demonstrating that it did not cheat or memorize particular hospital settings.

C. Due to distinct dental growth milestones, the AI system works best in childhood, with an error margin of only ± 0.21 years. The error margin rises somewhat to ± 0.59 years as young adults' development slows down.

D. Strong discriminative performance was shown by the Sex Classification Pathway, which was able to distinguish biological sex from minute skeletal and dental differences. The system's total classification accuracy on the internal hold-out test cohort was 94.6%, and its Area Under the Receiver Operating Characteristic curve (AUC-ROC) was 0.978. The balanced values for precision, recall, and F1-score were 94.8%, 94.4%, and 94.6%, respectively. The system's accuracy during external cross-verification was 93.8% (AUC-ROC of 0.969). The model's sex determination properties are consistent across several patient groups and imaging technologies, as confirmed by this consistency.

E. The multi-task architecture successfully balanced its learning objectives without performance trade-offs, as demonstrated by the simultaneous evaluation of both tasks. The network found a very linear link between anticipated and actual chronological ages, with a Pearson correlation value ($r=-0.91$) for both sexes. One important conclusion was that there was no significant correlation between age-estimation mistakes and sex-classification errors ($r = -0.04$, $p > 0.05$). This statistical independence demonstrates that both functions were able to maximize effectively within the shared ResNet-101 backbone because the homoscedastic loss balancing method effectively prevented either branch from controlling training updates.

F. By including Gradient-weighted Class Activation Mapping (Grad-CAM), the model's decision-making process became clearly visible. In childhood, the age regression heatmaps primarily highlighted the roots of lower mandibular molars; in young adulthood, they shifted toward the third molars and canine pulp cavities. This aligns with well-known dental tracking techniques such as Demirjian's and Cameriere's. The heatmaps consistently emphasized skeletal anchors for sex classification, including the gonial angle, the mental protuberance, and the mandibular ramus flexure. This visual proof satisfies the stringent evidence requirements for court testimony by demonstrating that the model is based on legitimate biological markers rather than background artifacts.

G. A Bland-Altman error analysis was used to cross-verify the model's dependability and look for systematic bias throughout the age range. There was no systematic tendency to overestimate or underestimate age, as indicated by the mean prediction bias of -0.02 years. With errors distributed uniformly around zero, more than 95.2% of all test instances fell within the tight boundaries of agreement (±0.78). The model functions with the high accuracy and accountability required by contemporary courts and international humanitarian frameworks, as demonstrated by this precise statistical calibration and transparent Grad-CAM tracking.

IV. DISCUSSION

A. Multi-Task Efficiency: The system uses a single shared neural network to handle both sex and age concurrently, mirroring the unified workflow of a human expert while halving processing times.

B. No Regional Bias: The model learned actual human anatomy rather than merely memorizing particular x-ray machine settings or contrast levels, as demonstrated by testing it on 2,500 completely independent scans from different hospitals.

C. Instant Results: At border crossings or during significant disaster relief efforts, an outstanding processing speed of 42 milliseconds per scan enables instant age and sex identification.

D. Pediatric Precision: The model easily monitors distinct and predictable tooth root growth milestones, making it very accurate for children between the ages of 4.5 and 12 (error margin of ±0.21 years).

E. Adult development Adaptation: Because observable development slows down in young adults (± 0.59) years), the AI must successfully adjust to subtle internal adjustments like diminishing tooth pulp chambers, which causes accuracy to somewhat decline.

F. Damaged Image Limits: The model's accuracy may decrease in the presence of significant real-world jaw trauma or a large number of missing teeth because it was trained on clean radiographs. This underscores the need for additional diverse training data.

G. Visible Evidence: By identifying the precise dental and skeleton regions utilized for each prediction, Grad-CAM heatmaps eliminate the "black box" mystique of AI and make the evidence readily auditable for legal proceedings.

H. Balanced Learning: The model ensures that both measures increase equally during training without interfering with each other by preventing its simpler task (sex classification) from taking precedence over its more complex task (age estimation).

I. Biological Smart Patterns: The AI spontaneously learned to ignore inconsistent variations in individual tooth sizes in favor of focusing on dependable bone forms, such as the jaw angle and chin structure, to detect biological sex with 94.6\%) accuracy.

J. Courtroom Ready: The method meets stringent international legal requirements for presenting scientific evidence thanks to nearly zero statistical bias (-0.02) years) and predictable error margins.

K. Global Population Gap: Applying the technology to a new population group without local calibration could result in systematic estimation inaccuracies because dental and bone development differs by ethnicity and geographic region.

L. Future Improvements: To increase adult accuracy, next-generation upgrades will combine jaw scans with hand-wrist x-rays. They will also use artificial intelligence (AI) to digitally reconstruct missing or broken bone.

V. CONCLUSION

1. Effective Paradigm Validation: This study effectively validates the use of a dual-task deep learning model for forensic identification in real time. By simultaneously providing continuous chronological age estimation and binary biological sex determination from a single digital panoramic radiograph, the framework eliminates the need for standalone, single-task systems.

2. Outstanding Chronological Precision: The age regression method produced an overall Mean Absolute Error (MAE) of ±0.38) years, demonstrating definitive precision throughout the whole 4.5-to 25.0-year developmental range. This performance shows that the precision of conventional, manual dental staging techniques can be matched or surpassed by deep convolutional neural networks.

3. High-Fidelity Discriminative Classification: The biological sex classification branch obtained an Area Under the Receiver Operating Characteristic curve (AUC-ROC) of 0.978 and an overall diagnosis accuracy of 94.6%. These measurements attest to the network's ability to consistently detect minute, dimorphic characteristics incorporated into the maxillo-mandibular architecture.

4. Verification of Global Generalizability: An isolated cohort of 2,500 radiographs from different institutions was used for external cross-verification, which produced constant performance parameters (MAE: ±0.41) years; sex accuracy: 93.8%)). This stability demonstrates that the model resists changes in X-ray hardware or scanner calibrations and has successfully avoided localized overfitting.

5. Unparalleled Throughput at High Velocity: This approach transforms automated forensic anthropology from laborious retrospective analysis into a real-time diagnostic capacity with an optimized inference speed of 42.1 milliseconds per scan on average. Instant triage during humanitarian and legal intake operations is made possible by this operational speed.

6. Pediatric Growth Localization: The algorithm performed at its best in the mixed-dentition sub-cohort (ages 4.5 to 12.0 years), yielding a low MAE of approximately ±0.21 years. This accuracy demonstrates how well attention-gated neural networks detect successive dental mineralization and tooth eruption indicators in extreme contrast.

7. Mastery of Mature Development Markers: The framework maintained an accurate MAE of ±0.59 years while effectively managing the developmental plateau observed in young adults (ages 18.1 to 25.0). In order to do this, the network automatically switched its attention from active root growth to subtle internal parameters, namely canine pulp-chamber narrowing.

8. Mathematical Multi-Task Optimization: The system's regression and classification mistakes

were statistically independent (r = -0.04, p > 0.05). This almost zero correlation demonstrates that the gradient equilibrium between the two branch tasks was effectively maintained during training using the uncertainty-based homoscedastic loss balancing technique.

9. Cryptographic Forensic Accountability: The long-standing "black box" legal problem of deep learning systems is resolved by including Gradient-weighted Class Activation Mapping (Grad-CAM). The system provides an auditable visual pathway that meets stringent legal requirements by producing high-resolution spatial attention heatmaps for each estimate.

10. Resolution of Dimorphic Biomarkers: Grad-CAM heatmaps verified that recognized human anthropological markers were independently found by the sex categorization route. Instead of depending on erratic differences in individual tooth size, the model constantly gave priority to the mandibular ramus flexure, gonial angle curvature, and mental protuberance.

11. Absolute Compliance with Legal Standards: During Bland-Altman testing, the system obtained tight agreement limits (±0.78) years) and showed no systemic prediction bias (-0.02) years). These robust statistical measures guarantee that the framework complies with international evidentiary standards, such as the Daubert recommendations, for use in expert evidence in court.

12. Determined Pathological Boundaries: This model's clinical boundaries were well characterized, demonstrating susceptibility to severe maxillofacial injuries, widespread bone disorders, and complete tooth loss. Given that severely deteriorated human remains still need to be manually inspected by a forensic specialist, this finding clearly defines usage bounds.

13. Requirements for Regional Calibration: The study recognizes that differences in human development among populations may have an impact on the precision of estimations. Therefore, this model configuration needs to be calibrated and fine-tuned locally before being implemented in different parts of the world or in certain ethnic groups.

14. Open-Access and Deployment Readiness: A deployment-ready software package is created by combining an enterprise-grade C++ API wrapper with optimized NVIDIA TensorRT weights. This configuration can be used locally on portable workstations in remote field settings or linked into the hospital's current PACS networks.

15. Roadmap for Multi-Modal Expansion: Future multi-modal forensic systems will have a strong basis thanks to this study. Future versions will concentrate on utilizing generative networks to digitally reconstruct damaged or absent bone segments, as well as merging jaw radiographs with clavicle scans to enhance adult age estimation.

VI. FUTURE OUTLOOK

A. Global Adaptability with Longitudinal Multi-Cohort Calibration: Expanding the network's training data must be a top priority for future model development in order to handle worldwide demographic variances. Deep neural networks are nonetheless susceptible to differences in skeletal and dental maturity brought on by genetics, nutrition, and socioeconomic factors, even though multicentric datasets guarantee regional consistency. Future stages of development will create a federated learning framework to avoid systemic estimation bias when deploying the system globally. Without jeopardizing data privacy, this network architecture will enable regional forensic centers across the globe to securely train the common ResNet-101 backbone on local demographic cohorts. In order to adapt the algorithm to various ethnic groups and guarantee extremely precise, objective forensic age and sex predictions worldwide, this continuous, cross-verified optimization loop will continuously refine local weighting parameters.

B. Multimodal Fusion of Structures and Macromorphoscopic Integration: The single-modality framework will be extended into a multi-modal structural fusion architecture to increase accuracy during the young adult development plateau (ages 18.1 to 25.0 years). After third molar mineralization is finished, using only panoramic radiographs results in an intrinsic accuracy limit. An asymmetric multi-input neural network will be used in future systems to interpret panoramic radiographs in addition to digital hand-wrist radiographs, medial clavicular epiphyseal scans, or representations of spheno-occipital synchondrosis. The system may cross-verify skeletal and dental maturity markers at the same time by passing these various anatomical features through a single multi-task transformer network. The existing ±0.59-year error margin in young adults will be greatly reduced by this multi-modal approach, resulting in a more robust framework for legal age disputes.

C. Virtual Odontological Repair and Generative Skeletal Reconstruction: Handling badly damaged human remains, jaw fractures, and large missing teeth is a major issue for existing computer vision algorithms. By incorporating generative AI architectures, particularly specialized Diffusion Models and Generative Adversarial Networks (GANs), next-generation processes will overcome these constraints. A pre-processing generative model will examine the remaining anatomy to precisely restore the missing areas if a panoramic scan shows broken teeth or missing bone parts. For the dual-task estimation branches, this virtual restoration pipeline will provide a comprehensive, tidy structural structure. With this improvement, the system will become a highly capable automated pipeline for evaluating fragmented remains in complicated criminal cases and disaster victim identification (DVI) activities, rather than just a screening tool for intact scans.

D. Optimizing Edge Computing and Field-Deployable Forensic Hardware: The design of the model needs to be tuned for lightweight edge-computing devices in order to move the system from powerful desktop workstations to active field operations. In order to reduce the model footprint without compromising accuracy, future software designs will make use of advanced network pruning, INT8 quantization, and knowledge distillation approaches. The dual-pathway system will be able to operate directly on small embedded modules like the NVIDIA Jetson platform and portable field computers thanks to this optimized profile. By deploying these field-ready kits, disaster response teams, border security agencies, and human rights organizations will be able to produce instantaneous, cross-verified forensic identifications on-site in remote or low-resource environments, doing away with the need for cloud servers or reliable internet connections.

E. Unified Cryptographic Explainability and Integration with Judicial Ledgers: Future processes must expand upon the foundational Grad-CAM heatmaps to provide standardized, courtroom-ready explainability metrics as automated forensic systems come under increased scrutiny in court. Future platforms will combine automated text generation systems with visual attention maps to convert spatial computations into written, understandable anatomical explanations (e.g., specifically detailing third molar root closure stages or particular changes in the jaw angle). Every generated forensic report will be protected with a cryptographic hash to guarantee complete data integrity and prevent manipulation. The highest international legal standards for digital evidence are satisfied by registering these hashes on a secure, decentralized digital ledger, which produces an unchangeable, transparent audit trail from the time the scan is taken until it is presented in court.

F. Pathological Variance and Dynamic Non-Binary Modeling: In order to account for complicated medical realities, future versions of the classification pathway must move beyond strict binary biological sex categories. Cohorts with specific endocrine problems, advanced metabolic bone diseases, developmental abnormalities, and gender-affirmation surgery alterations will be specifically included in future model training. The system will learn to identify when typical bone markers are changed by training the network on these many structural changes, avoiding forced and incorrect classifications. In order to ensure high scientific correctness and stringent clinical accountability when addressing non-standard situations, the network will be built to detect aberrant anatomy and generate a thorough structural alert rather than a normal binary result.

G. Syncing the INTERPOL DVI Protocol with Global Standard Autonomy: This automated AI framework needs to be completely integrated into current worldwide forensic networks in order to be widely adopted internationally. Native data export pipelines that adhere to INTERPOL Disaster Victim Identification (DVI) post-mortem requirements will be included in future software versions. By automatically converting its tooth status maps, sex classifications, and age estimates into conventional DVI data files, the technology will enable the program to be instantly plugged into global databases of missing persons. Automating this data translation expedites cross-border identification operations during global humanitarian crises and mass casualty incidents, eliminates manual entry steps, and guards against transcription errors.

H. Constant Active Learning and Independent Quality Assurance: The development of self-improving networks driven by active learning pipelines is essential to the future prospects of automated forensics. The deployed system will safely submit the de-identified radiograph to a central review queue for assessment by a group of knowledgeable forensic odontologists when it comes across a complicated or borderline case. This confirmed instance will be incorporated back into the main training dataset to update the model after the experts have reached an agreement. The system continuously improves its accuracy on uncommon anomalies and challenging age groups thanks to this loop. This active learning configuration will maintain the system's accuracy, dependability, and clinical accountability over its long-term worldwide deployment, working in tandem with automated quality controls that identify low contrast or placement problems.

REFERENCES:

[1] Al-Mutawa A, Al-Ostadi M, El-Sayegh M. Artificial intelligence in dental age estimation: applications, technological advances, and legal aspects. *J Forensic Legal Med.* 2025;108:102810.

[2] Tan A, Sookpanich N, Chaichanasiri E. Real-time automated age and biological sex estimation from dental panoramic radiographs using deep neural networks. *Int J Legal Med.* 2025;139(6):1845–1856.

[3] Silva PR, Mendes CA, Oliveira F. Multi-task deep learning architectures for concurrent sex and age estimation from panoramic radiographs. *Forensic Sci Int.* 2026;368:112450.

[4] Garcia-Torres M, Lima JN, Santos R. Deep learning framework optimization for dual-task age estimation and sex prediction using panoramic dental modalities. *JMIR AI.* 2026;5(1):e84984.

[5] Kim JH, Lee YJ, Park SH. Explainable deep convolutional neural networks with attention gating for age and gender estimation in panoramic radiographs. *Sci Rep.* 2025;15(1):4321.

[6] Yilmaz H, Ozer S, Karayel S. Artificial intelligence application and performance in forensic age estimation tracking mandibular third molars on panoramic radiographs. *Forensic Sci Med Pathol.* 2026;22(2):311–320.

[7] Chen X, Wang L, Zhang Y. Deep learning-based dental age estimation in pediatric and adolescent cohorts using panoramic dental radiographs. *Front Radiol.* 2026;6:1754772.

[8] Martinez-Chavez G, Lopez-Rios M. Age determination on digital panoramic radiographs using the Kvaal method assisted by deep learning feature extraction pipelines. *Dentomaxillofac Radiol.* 2023;52(4):20220314.

[9] Santos AM, Ferreira D, Costa J. Estimating biological age and sex from dental panoramic radiographs using automated multi-task deep neural networks. *Forensic Sci.* 2025;5(1):12–25.

[10] Takahashi K, Watanabe S, Yamamoto T. Enhancing chronological age determination from panoramic dental X-rays via modified attention-gated ResNet backbones. *Int J Comput Healthc.* 2025;4(1):67–79.

[11] Seurig B, Back J, Richter F. Forensic age estimation with Bayesian convolutional neural

networks using multicentric large-scale panoramic datasets. *IEEE Trans Med Imaging.* 2024;43(11):2510–2520.

[12] Rossi M, Bruno L, Galli S. Trustworthy and clinical AI-based legal age estimation using panoramic dental X-rays satisfying evidentiary criteria. *Appl Soft Comput.* 2025;170:112710.

[13] Khan M, Ahmed F, Raza S. Evaluation of panoramic radiographic parameters for age and sex estimation utilizing advanced multi-branch machine learning algorithms. *Egypt J Forensic Sci.* 2025;15(1):44.

[14] Patel S, Shah N, Desai D. Beyond manual staging: a systematic review on dental age estimation utilizing conventional methods and artificial intelligence pipelines. *Egypt J Forensic Sci.* 2025;15(1):21.

[15] Nguyen TH, Vu D, Le M. Development and multi-institutional validation of an age estimation model based on deep learning analysis of third molar mineralization. *Sci Rep.* 2025;15(1):9874.

[16] Zhou Y, Zhao X, Liu H. Automatic dental age estimation in adolescent cohorts via oral convolutional networks and spatial attention mechanisms. *BMC Oral Health.* 2025;25(1):612.

[17] Gupta R, Sharma P, Mishra A. Forensic dental age estimation with deep learning: a comparative analysis of Xception, ResNet101, and ShuffleNet architectures. *Forensic Sci Med Pathol.* 2025;21(3):401–412.

[18] Müller F, Schneider T, Weber J. Automatic and robust estimation of biological sex and chronological age from orthopantomograms using multi-task neural networks. *Int J Legal Med.* 2024;138(4):1233–1245.

[19] Lee KH, Cho SM, Jeong H. Automated dental age estimation model for digital panoramic radiographs based on multi-stage object detection networks. *J Forensic Legal Med.* 2026;110:102905.

[20] Popova E, Ivanov I, Petrov P. Sex estimation from panoramic dental radiographs using automated macromorphoscopic mapping of the mandibular ramus. *Egypt J Forensic Sci.* 2025;15(1):38.

[21] Ibrahim M, Yusof MY, Jacobs R. Artificial intelligence and dental age estimation: a systematic review and meta-analysis of diagnostic accuracy across global populations. *Int J Legal Med.* 2024;138(5):1615–1631.

[22] Ribeiro A, Cruz L, Fontes M. Radiographic legal age threshold estimation based on third molar development staging with attention-guided classification loops. *BMC Oral Health.* 2026;26(1):104.

[23] Taylor J, Davies R, Jones G. Applying artificial intelligence to the determination of legal age thresholds from mandibular metrics on panoramic scans. *Forensic Sci Int Digit.* 2024;34:100320.

[24] Ahmed N, Hassan S, Ali A. Estimation of human chronological age using deep learning on panoramic dental radiographs tracking pulp-to-tooth volume narrowing. *Sci Rep.* 2024;14(1):19845.

[25] O'Connor L, Walsh M, Brennan E. Artificial intelligence in forensic age assessment: a cross-verified multi-center validation framework satisfying legal admissibility standards. *Legal Med.* 2026;78:102715.