Journal of Indo-pacific Academy of Forensic Odontology

Vol. 14 (2), (2025) 13-18

https://jinpafo.in/

REVIEW ARTICLE

Artificial Intelligence & Deep Learning in Forensic Odontology: From Automated Age-Estimation to Dental Identification

Arushi Tomar[1], Shivani Kumari[1], Mosharraful Islam[1], Shalini Gupta[2*]

Abstract

Introduction: Forensic odontology plays a pivotal role in human identification, age estimation, and bite mark analysis. The rapid integration of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized data-driven forensic workflows, offering enhanced accuracy, speed, and reproducibility.

Material and Method: To systematically map and synthesize the scope, applications, and trends in AI and DL for forensic odontology, from automated age estimation to dental identification the scoping review was done following the PRISMA-ScR guidelines. Searches were conducted across PubMed, Scopus, Web of Science and Google Scholar up to August 2025 using keywords "Artificial Intelligence", "Deep Learning", "Forensic Odontology", "Age Estimation" and "Dental Identification". Eligible studies included original research, reviews and reports in English language involving AI/DL applications. Data were charted and synthesized accordingly.

Results: From 486 initial records, 26 met inclusion criteria. Convolutional Neural Networks (CNNs) were the most utilized architecture for dental radiograph analysis. Applications were clustered into: (i) Automated age estimation , (ii) Sex determination, (iii) Dental identification and (iv) Bite mark pattern recognition. Reported accuracies for age estimation ranged from 85% to 97%.

Conclusion: Transfer learning and hybrid models showed increasing adoption post-2020. AI and DL show high potential in forensic odontology, with CNN-based models dominating the landscape. However, challenges in dataset standardization, model validation across populations, and legal admissibility remain. Future research should focus on explainable AI and cross-population generalizability.

Keywords: Forensic science , Artificial Intelligence, Deep Learning, Age estimation, Dental

Introduction

The Latin term *forensis*, which means "pertaining to the forum," is the root of the English word "forensic." Odontology refers to the study of the teeth and it in effect denotes dentistry. Therefore , according to the Federation Dentaire Internationale (FDI) Forensic Odontology," that branch of Dentistry, which in the interest of justice, delas with the proper handling and examination of dental evidence and with proper evaluation and presentation of dental findings."[1] It plays a crucial part in identifying the remains of victims, including those of mass disasters and bioterrorism as well as those who have been burned, maimed, or deteriorated. The value of forensic odontologists in identifying victims of industrial strikes, aviation mishaps, natural disasters, and terrorist attacks—whether they involve explosives, chemicals, radiological, or nuclear weapons—has also been highlighted by catastrophic events. These events can be isolated or widespread. When it comes to decayed, burned, or skeletonized bodies, forensic odontology is essential when traditional identification techniques like fingerprints and visual recognition are not possible.[2] Traditional methods often rely on subjective interpretation, are time-consuming and therefore require specialized expertise.

A common definition of artificial intelligence (AI) is a tool that includes any methods that allow computers to behave like humans and outperform humans in making decisions to complete difficult tasks on their own or with little assistance from humans.[3] Understanding the differences between artificial intelligence, deep learning, machine learning, and

[1]Junior Resident Department of Oral Pathology & Microbiology, King Georges Medical University, Lucknow 226003 India

[2]Professor & Head, Department of Oral Pathology & Microbiology, King Georges M edical University, Lucknow 226003 India

***Corresponding Author:** Shalini Gupta, Professor & Head, Department of Oral Pathology & Microbiology, King Georges M edical University, Lucknow 226003 India, E-Mail: dr.shalni@gmail.com

How to cite this article: Tomar A, Kumari S, Islam M, Gupta S. Artificial Intelligence & Deep Learning in Forensic Odontology: From Automated Age-Estimation to Dental Identification. Journal of Indo-pacific Academy of Forensic Odontology. 2025;14(2):13-18. doi: 10.53275/jinpafo.v14.i2.04

Source of support: Nil

Conflict of interest: None.

https://doi: 10.53275/jinpafo.v14.i2.04

Received: 13/12/2025 **Accepted:** 01/04/2026 **Published online**: 15/04/2025

data science is crucial to understanding artificial intelligence. Despite their connections, each of these professions has distinct qualities of its own .[4] In contrast, data science uses all of these disciplines to glean information and insights from data. In order to learn from large datasets, deep learning, a branch of artificial intelligence, uses neural networks that are modelled after the structure of the human brain. Deep learning algorithms are capable of making predictions or judgments by automatically recognizing and extracting features from unprocessed data, such as text, sounds and images.[5] Natural language processing, audio recognition and image recognition are notable uses of deep learning. Another area of artificial intelligence is machine learning, which focuses on creating statistical models and techniques that let computers learn from data without the need for explicit programming. Predictive modelling, fraud detection and recommendation systems are examples of machine learning use cases. In order to get insights and information from data, data science, an interdisciplinary field, combines computational and statistical methods with specialist knowledge in a number of fields.[6] Data collection, cleaning and preprocessing, exploratory data analysis, statistical modelling and machine learning are just a few of the many tasks it includes. Applications of data science can be found in many different industries, including e-commerce, social media, healthcare and finance .[7]

Numerous medical and dental specialties have long made use of artificial intelligence. Radiology , diagnosis and treatment of a variety of illnesses and ailments, clinical decision-making support, personalized medicine , chronic disease monitoring , predictive analysis and of course, a plethora of medical research .[8] are among its many applications in medicine. Dental radiology, dental diagnostics , dental therapy planning, orthodontics, dental prosthodontics ,periodontology, endodontics, oral pathology , dental implantology, dental robotics and other dental specialties are just a few of the many dental domains that use artificial intelligence.[9] Pertaining to forensic odontology, increasing studies have now focused on generating models for age estimation as well as comparative and reconstructive dental identification across the globe. AI systems trained on dental radiographs, photographic evidence, and dental charts have shown promising accuracy in age estimation, sex determination and matching ante-mortem to post-mortem records. DAE (Dental age estimation) plays a central role in Forensic odontology for human identification. Recent research focused on improving DAE methods by integrating traditional expertise with machine learning and deep learning (DL) models, significantly improving accuracy and expanding applications in clinical dentistry, legal proceedings and healthcare.

Thereby, the present scoping review systematically maps the existing literature on AI/DL in forensic odontology and its application in age estimation as well as identification of the individual , identifies research gaps and proposes future directions in the field.

Objectives

The primary objective is to systematically map and summarize current applications of AI and DL in forensic odontology, focusing on:

- Automated age estimation.
- Sex determination.
- Dental identification in DVI.
- Bite mark analysis.
- Emerging applications such as dental-based facial reconstruction.

Material And Method

PROTOCOL

This study is a scoping review conducted in accordance with the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Scoping Reviews) guidelines (Fig.1.).The extensive grey literature search was done in search engines such as PubMed, google scholar. Key terms used for search included “artificial intelligence”, “Deep Learning”, “Forensic Odontology”, “Age Estimation” and “Dental Identification”.

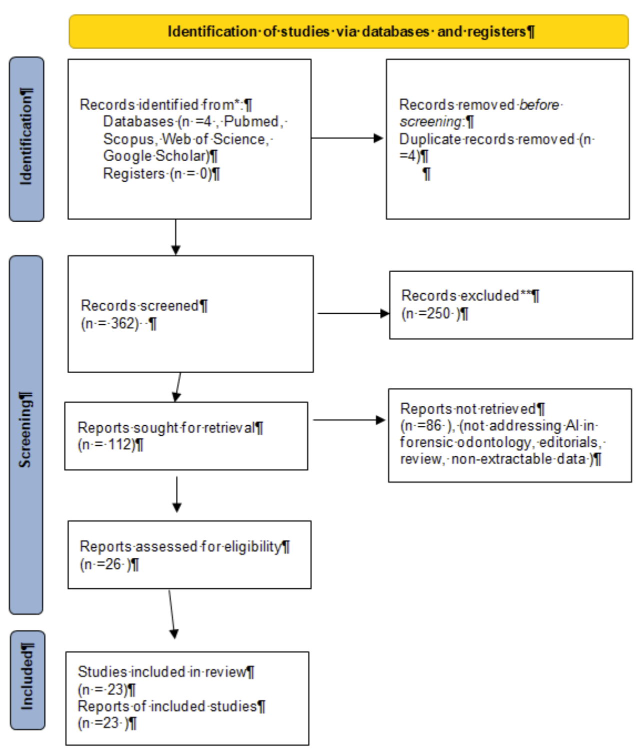

Fig.1: Flowchart of PRISMA Guidelines 2022 depicting the search strategy

Research articles have been included for analysis after filtering through the below-mentioned inclusion and exclusion criteria and after removal of duplicates by two independent reviewers. A narrative thematic synthesis was undertaken. Results were grouped into four major forensic applications.

Inclusion Criteria

- Peer-reviewed primary studies (experimental, observational, proof-of-concept).
- Studies using AI/DL models (ML, CNN, GAN, transformers, etc.).
- English-language publications.
- No date restriction.

Exclusion Criteria

- Studies without AI/DL methodology.
- Non-forensic dental studies.
- Reviews, editorials, and opinion pieces.

Data Extraction and Synthesis

Data were extracted independently by two reviewers and synthesized using a narrative thematic approach. Studies were categorized into four major domains:

- Age estimation
- Sex determination
- Dental identification
- Bite mark analysis

Results

Search Outcome

- Records identified: 486
- After duplicates removed: 362
- Full-text screened: 112
- Studies included: 26

Study Characteristics

- Geographical spread: Asia (42%), Europe (28%), North America (20%), Others (10%)
- Most common data type: panoramic radiographs (OPG), followed by intraoral photographs and CBCT scans.
- CNNs were the most frequent architecture, with VGGNet, ResNet and Inception variants are widely used.

Discussion

Artificial neural networks, deep neural networks, and machine learning algorithms are three crucial topics that must be well defined. There are distinctions between these terminologies even if they are similar. The hierarchical link between the concepts exists . AI research first concentrated on formal languages with hard-coded statements, and a computer could automatically consider applying rules for logical reasoning .[10] Thankfully, machine learning can get over these restrictions. ML typically refers to the notion that a computer program performs better over time, as measured by a set of tasks and performance metrics.[11] Therefore, automating the creation of analytical models to perform cognitive tasks like pattern recognition or object classification is its primary goal. The objective can be achieved by using algorithms that can learn iteratively from training data tailored to a particular problem. Thus, without programming, computers are able to recognize intricate patterns and hidden information. When it comes to high-dimensional data tasks like classification, regression, and clustering, machine learning exhibits good applicability.

Depending on the learning task, the discipline offers different kinds of machine learning algorithms. The specifications and variations of Bayesian approaches, decision trees, instance-based algorithms, regression models, and artificial neural networks (ANNs) vary.[12] In supervised learning, the algorithm “learns” from the training dataset by making data predictions and iteratively adjusting for the right response. This is the primary difference between the two methods. Although supervised learning methods outperform unsupervised learning models in terms of accuracy, correctly labelling the data requires human interaction [13] The input, hidden, and output layers make up the fundamental ANN architecture .[14] The input neurons that transmit the data or signal to the hidden layer are usually found in the input layer. Only when the transmitted signals above certain threshold values established by an activation function will the neurons in the buried layer process or fire the signals to the subsequent neuron. This layer, which may have zero or more hidden layers, is helpful for learning a non-linear mapping between input and output. Lastly, the output layer produces ultimate outcomes like binary input categorization or image classification .[15]

AI in Forensic Odontology

In terms of delivering trustworthy data for forensic scientific decision-making, the use of the AI-based approach in forensic odontology has shown to be revolutionary. Therefore, we showed in these studies that there are currently four main domains that successfully use AI technology: dental comparison ,sex determination ,age estimation and human bite marks.

Dental Comparison

A crucial component of forensic identification is establishing a person’s identity. It is difficult for forensic investigators to identify victims of a major tragedy effectively and efficiently by examining the human identifiers that are accessible. A more successful and efficient identification procedure may be attained with the use of AI in forensic dental identification .[16] In order to facilitate individual identification, DL techniques like CNN and R-CNN have been developed and applied for automatic tooth detection on dental radiographs. Using deep neural networks, Choi *et al.*[17] investigated the automatic identification of teeth and dental treatment patterns on OPG. A CNN modified by EfficientDet-D3 was used as a pre-trained object detection network to detect dental treatment and natural teeth. The study found that CNN performed exceptionally well in automatically detecting implants (96.8%), prosthetics (80.6%), repaired root canals (81.2%), and natural teeth (99.1% precision).

A study by Heinrich *et al.*[18] suggested utilizing computer vision to automatically compare panoramic radiographs taken before and after death. The study's conclusions suggest that the suggested method, which has an average accuracy of 85%, may be a trustworthy way to compare antemortem and postmortem OPG. A maximum of 259 related points were obtained through systematic matching when two distinct OPGs belonging to the same individual were successfully identified, and a maximum of 12 points were obtained for other non-identical individuals.

Sex Determination

Because male and female teeth differ in morphology, crown size, and root length, forensic odontologists can assist other specialists in determining the sex of the remains by using the features of the teeth and skull. Furthermore, the two sexes had different skull patterns and traits. As a result, this will help forensic odontologists identify the remains' sex. Various dental techniques, including cheiloscopy, the palatal rugae ,the mandible and sinuses, can be used to study sexual dimorphism. Thus, this will assist forensic odontologists in determining the sex of the individual.[19] Computer science approaches like ML, ANN, and DL are potential ways to automate the traditional procedure and improve repeatability, especially as automation trends in the medical industry have been receiving a lot of attention. ML approaches for sex determination have been used in a number of published research. A fully automated method for determining a person's sex from photos of their maxillary tooth plaster was proposed by Akkoç *et al.*[20] Prior to the segmentation and classification stage, the picture acquisition procedure is completed. The camera angle is fixed on top of the mechanism, and cube-shaped light sources are installed to absorb light from all directions in order to first produce a standard image. In the meantime, Patil *et al.*[21], have proposed a study that uses digital panoramic radiographs and mandibular morphometric data. Seven morphometric criteria were chosen in light of earlier research. This paper proposes a feed-forward neural network using a backpropagation learning technique. With 70% of the dataset allocated for training, 15% for validation, and 15% for testing, the NN model is composed of an input layer, two hidden layers, and one output layer. According to the three morphometric parameter analyses, ANN analysis outperformed both discriminant analysis and logistic regression, which both had an overall accuracy of 69.9%, with a better overall accuracy of 75%.

Using dental x-ray pictures, Nithya and Sonam .[22], published a thorough study that included concise descriptions of deep convolutional neural networks (DCNN). Five levels of sequential networks make up the authors' original CNN architecture, with the last layer being fully connected. The hyperparameter values are mentioned in this study. For instance, the method is given batch size 50, Adam optimizer, and category cross-entropy loss. This led to a 95% accuracy rate. The authors claimed that their suggested approach outperformed the current one, which made use of transfer learning using a VGG16 model that had already been trained.

Age Estimation

By using pattern recognition and classification techniques to the target pictures, De Tobel *et al.*[23] , presented an automated method for estimating age based on the development of the mandibular third molar using panoramic radiographs. First, the Photoshop software was used to crop the ROIs, which show the third molar, and equalize the image contrast for all data. A pre-trained model of the AlexNet network was then used, and the accuracy, Rank-N recognition rate, mean absolute difference, and linear kappa coefficient were obtained using various validation metrics in a 5-fold cross-validation scenario.

Another study was done by Banar et al.[24], which utilised third molar developmental stages for age estimation by using fully automated system. Three primary processes—third molar localization, segmentation, and classification—are suggested by supplying the ground truth images. A YOLO-like CNN architecture is used in image localization to predict the geometrical center within the ground truth image cell. The ImageNet pre-trained modal was used to identify the rectangular ROI, which is where the third molar was visible on the original input image. The retrieved ROI was then segmented using a second CNN. Using two distinct CNN architectures—a basic CNN with 10 layers and the more intricate DenseNet201—a final CNN integrates the third molar's ROI and segmentation to categorize the third molar's developmental stage. Furthermore, the authors stated that since the age estimation stage was left out of the suggested framework, future studies should incorporate it rather than concentrating on the suggested three-step process.

Human Bite Marks

Human bite mark analysis using machine learning techniques is still in its infancy. The majority of earlier techniques, ranging from fully automatic to semi-automated, concentrate on computer vision systems that make use of image processing algorithms. The increasing skepticism regarding the accuracy of bite marks as evidence in court is one of the reasons why academics and professionals are not paying much attention to this topic. There has been a shift from general skepticism to broad credulity regarding bitemark comparisons' capacity to accurately identify the origin of a disputed bite mark, with skepticism becoming more prevalent.

Molina *et al*.[25], has presented the semi-automated study of human bite marks. DentalPrint uses 3D dental cast photos to create biting edges, while Biteprint is used to describe the biting edges. The ROC curve was used to assess the identifying procedure's performance. According to the authors, the Euclidean distance of lower tooth rotation had the highest area under the ROC curve (AUC) of 0.73. As a result, their suggested technique for measuring lower tooth rotation might be useful in forensic investigations and in identifying the people who left bitemarks. Furthermore, this work set a new standard for further research on the analysis of human bite marks.

Limitations

- Language restriction to English may exclude relevant data.
- Grey literature not extensively searched.

Conclusion

By improving accuracy, efficiency and reproducibility, artificial intelligence (AI) and deep learning (DL) have shown significant promise in revolutionizing forensic odontology. According to this scoping review, Convolutional Neural Networks (CNNs) are the most popular models, especially in radiographic analysis, with claimed accuracy rates of 85–97% in dental age estimate, frequently outperforming conventional techniques. AI applications have grown beyond age prediction to include sex determination, dental recognition, and new fields like facial reconstruction. Recent developments show that hybrid models and transfer learning are becoming more popular, which enhances model performance to a greater extent. Nonetheless, a number of issues still exist, such as the absence of standardized datasets, restricted validation across various demographics, and worries about legal admissibility in forensic practice. It will be crucial to overcome these constraints by creating explainable AI models, huge multi-center datasets, and reliable validation methods. When all factors taken into account, AI-driven methods have great potential to develop forensic odontology into a more impartial, quick, and reliable discipline.

Declaration

- Patient consent: NA
- Ethical approval: NA

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