https://doi.org/10.48047/AFJBS.6.13.2024.7216-7248

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

From Pixels to Prosecution: Exploring the Role of Artificial Intelligence in Medico-Legal Investigations

Bharti Devi[1], Shivam Dwivedi[2*]

[1] M.Sc. Student, Department of Forensic Science, University Institute of Allied Health Sciences (UIAHS), Chandigarh University, Mohali, Punjab, India. Address - Department of Forensic Science, University Institute of Allied Health Sciences (UIAHS), Chandigarh University, Mohali, Punjab, India. Phone Number - +918307447919

E-mail – bhartisaini62732@gmail.com

[2*] Assistant Professor, Department of Forensic Science, University Institute of Allied Health Sciences (UIAHS), Chandigarh University, Mohali, Punjab, India.

[*]**Corresponding Author** Mr. Shivam Dwivedi

Address - Department of Forensic Science, University Institute of Allied Health Sciences (UIAHS), Chandigarh University, Mohali, Punjab, India. Phone number- +918827548677

E-mail- shivamdwivedi204@gmail.com

Volume 6, Issue 13, Aug 2024

Received: 15 June 2024

Accepted: 25 July 2024

Published: 15 Aug 2024

doi: 10.48047/AFJBS.6.13.2024.7216-7248

Abstract

Forensic medicine is the application of medical knowledge in the legal scenarios to help the court of law in providing justice to innocent individuals. It encompasses several applications including criminal investigations, human remains identification, evaluation of trauma and injury, sexual assault cases, facial reconstruction, and Post-mortem interval estimation (PMI). The traditional methods used in this field involve autopsy, collection of viscera, histopathological examination, etc. which have been the cornerstone of forensic investigations for decades. In the modern world, the emergence of Artificial intelligence (AI) has revolutionized forensic practices, offering enhanced capabilities in evidence analysis, pattern recognition, and decision-making processes. AI-based methods exhibit superiority over traditional approaches as they are capable of processing huge datasets rapidly, identifying complex patterns that go unnoticed by human perception, and minimizing human error. Moreover, AI facilitates the automation of routine tasks, thereby accelerating the investigative process and intensifying the accuracy and reliability of forensic analyses. This review paper highlights the transformative potential that AI holds in the field of forensic medicine, promising a new era of efficiency in legal proceedings and criminal investigations.

Keywords: Medical sciences, Forensic medicine, Artificial Intelligence, Machine Learning

Introduction

The medico-legal experts, anthropologists, odontologists, criminologists, and other specialists are among the professionals concerned with the investigation who look into and provide identification regarding individuals who have been injured or who have died because of unnatural or external causes. The cause of unnatural death can be poisoning, suicide, assault, or other violent crimes. Eventually, the findings are applied to assist the court of law in providing justice to the victims. This discipline is known as forensic medicine. In this field, the main motive lies in providing a detailed analysis report to the legal agencies regarding various aspects like PMI calculation, DNA analysis, age and sex identification, etc. Traditionally, forensic medicine experts performed investigations using only materials and human expertise. Unfortunately, these procedures were very complex and time-consuming resulting in human fatigue and inaccurate results. Furthermore, the accuracy and credibility of the results could be questioned by the court of law [1].

A significant problem in forensic science is the likelihood of biased results on the part of the forensic expert, who can generate forensic reports based on assumptions rather than thorough examination. Identification of suspects is the most important phase of an investigation that involves the greatest operational and ethical challenges. It must be carried out after a careful examination of all the available pieces of evidence and information. There is no protection from bias and manipulation since law enforcement agencies give conclusions based on experience and approximations that are neither reliable nor reproducible. Statistical evidence is often interpreted incorrectly in the court of law due to a lack of communication between scientists, investigators, and legal professionals which ultimately leads to judicial injustice. All these factors have made the application of AI to forensic medicine an appealing idea, and a lot of researches have been done in the recent years for the same [1], [2].

The comprehensive study of machines for understanding, simulating, and matching the mental as well as neural processes of human beings such as decision making, recognizing patterns, visual perception, learning, speaking and several other intellectual tasks is known as Artificial Intelligence or simply AI. It is also referred to as machine or computer intelligence. Being able to learn and apply knowledge and skills is an indication of intelligence. AI is the application of various concepts and methods from the domain of computer science, logic, mathematics, mechanics, and biology to make machines capable of doing activities that are currently restricted to only human ability [2].

AI has become more and more widespread in the work of researchers in recent years. The debate of whether AI has the potential to replace medical personnel has been the topic of discussion. Although the scientific community believes that such a replacement is not likely to occur shortly, forensic medicine experts can still use AI to help them in making more objective decisions or even to substitute human judgement in particular circumstances [3].

Artificial Intelligence as a new approach in forensic science

Forensic science applies the scientific principles, methods, and techniques for achieving justice in both civil and criminal cases. Among its seven basic principles, Locard's principle of exchange is one of the most prominent ones which states "When two entities interact, they leave traces on each other". This principle acts as a foundation in forensic science and criminal investigations and it extends to the field of AI as well, where even patterns can aid in suspect identification and help in moving proceedings from crime scenes to courtrooms [4]. Nowadays, AI is being applied to various branches of forensic science, such as forensic anthropology, odontology, dermatoglyphics, psychology, cyber forensics, and crime scene reconstruction. AI helps in making the investigative and analytical processes automatized. It also aids forensic experts and investigators through 3D reconstruction of the crime scenes, synthesis of logical evidence, efficient evidence management as well as its analysis to derive rational findings throughout various phases of the investigation process. AI-based methods help in analyzing large datasets for the identification of risks and are utilized to identify, inhibit, and even anticipate future criminal behaviour or crimes [5].

Artificial Intelligence as an emerging tool in forensic medicine

Due to the rise of AI in the field of forensic science, even forensic medicine couldn't resist its applicability. In India, various disciplines such as forensic anthropology, forensic odontology, forensic radiology, and forensic microbiology fall under the broad field of forensic medicine. Traditionally, the methods employed for carrying out the medico-legal investigations included Autopsy, Histopathological examinations, Collection of viscera, etc. that were entirely based on human analysis. Human dependency potentially made them error-prone due to a wide variety of factors like bias-related issues, longer turnaround times, the limited extent of human perception, etc [1], [2]. The emergence of AI-based methods has benefited medical examiners as they can make more impartial decisions or even replace human judgment in particular scenarios. AI is being incorporated in almost every domain of forensic medicine to analyze the huge amount of medical data generated by various analytical methods [3].

Applications of Artificial Intelligence and its advantages over the traditional methods:

1. Sex Estimation

In forensic medicine, the sex determination of a deceased person is the foremost priority during post-mortem examination to know the identity of the victim. Researchers are continuously searching for digital methods to estimate the identity of the sex more accurately. A lot of techniques have been utilized for this purpose.

In a study, the researchers compared the performance of 5 machine-learning techniques involving K-Nearest Neighbour (KNN), Naïve Bayes, Artificial Neural Network (ANN), Logistic regression, and Stochastic Gradient Descent (SGD) in sex determination using panoramic dental radiographs. Some anatomical points (13 measurements corresponding to the mandible) were considered for this purpose. Out of the 5 AI techniques employed, ANN showed the best performance with a sex estimation accuracy of 89%. However, the use of a limited number of panoramic radiographs confines the statistical credibility of the findings [6], [7]. Figure 1 shows a typical ANN architecture representing the main layers [8].

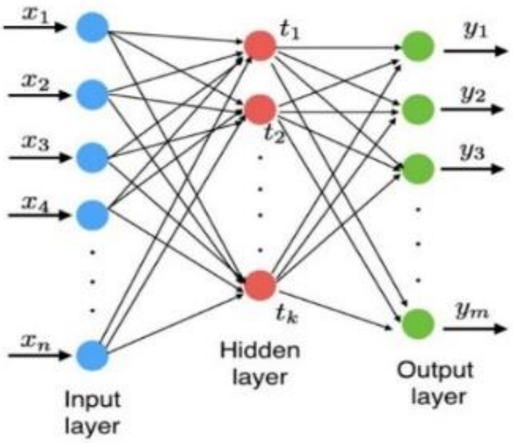

Figure 1. *General framework of an Artificial Neural Network (ANN) having 3 layers – input, hidden and output; the neurons from each layer are interlinked to the neurons in the succeeding layer.*

Manually collected mandibular morphometric parameters can also effectively improve the authenticity of the gender determination process. In the context of a study, a dataset comprising panoramic dental radiographs was analyzed using ANN. The observers were not aware of the subjects' sex at the time of measurement. Six different measurements including gonial angle, ramus height, bigonial width, corpus height, and condylar height were taken. These measurements were then employed to create a discriminant function to estimate the gender. The discriminant function showed an accuracy of 69.1%, revealing that the key measurements to estimate sex are the mandibular length, gonial angle, and bigonial breadth. The proposed model was compared with discriminant analysis and logistic regression, which were known for demonstrating strong results in gender determination. ANN performed better than the other two methods. The researchers concluded that manually obtained mandibular measurements can provide highly accurate results in forensic sex estimation [9], [10], [11]. In another study, a novel method called Dental Age and Sex Net (DASNet) that utilized a Convolutional Neural Network (CNN) path for the prediction of sex was introduced. The main focus was given to sex-specific features at different scales. Here, the estimated sex was used further for improving the process of age determination. The findings of this study were satisfactory but suggested further improvements [10], [11], [12].

In various researches, Computed Tomography (CT) scans have also been used for the purpose of sex estimation. In one such research, whole skull CT scans from an ethnic group (Known as Uighur) in northern China were utilized as the dataset. They employed an improved Backpropagation Neural Network (BPNN) for predicting sex on the basis of 6 cranial metrics: cranial sagittal chord, cranial sagittal arc, apical sagittal chord, apical sagittal arc, occipital sagittal chord and occipital sagittal arc. An accuracy of more than 94% was achieved by the neural network in determining the sex [13], [14]. Another study reported of using 3D morphometrics and virtual models to analyze cranial CT images of Czech adults. For studying the sex differences, frontal bone shape was the main parameter. The variation in the area of frontal bone from a fitted sphere was calculated and then utilized to identify the gender with an accuracy of 72.8%. However, compared to the other sex estimation methods with higher success rates, the proposed method was found to be less appropriate in Czech individuals [11], [15]. The sexually dimorphic ectocranial features can also be leveraged to differentiate between male and female individuals. Some researchers used these features to estimate sex from skeletal remains by employing a CNN on a dataset of skull images reconstructed from CT scans. The deep network achieved an accuracy of 95% when evaluated on new images of the skull. The findings demonstrated that AI methods are capable enough to eliminate the human bias associated with the gender estimation of osteological remains [11], [14], [16].

Cone Beam Computed Tomography (CBCT), a variant of traditional CT, is a valuable technique used particularly in dental and extremity imaging. The CBCT machine rotates around the human body and captures data utilizing a conical beam of X-ray. Recently, a combination of CBCT and AI for the determination of sex has proven to give more accurate and fast results. In a study, an AI-based 3D-Convolutional Neural Network (3D-CNN) was employed on a dataset of full-head 3D CBCT scans with a main focus on the thresholded soft and hard tissues. Automated 3D cephalometric landmark annotation areas were predicted along with soft tissue face estimation utilizing skull structure as well as reversed and facial growth vectors prediction [1], [17].

2. Age Estimation

Just like the sex determination of a deceased person, his/her approximated age also serves a significant role in streamlining the personal identification process. As per recent researches, teeth are capable enough of providing valuable information regarding the chronological age of a person. The developmental phase of various teeth can be observed with the help of dental radiographs to draw conclusions about the approximate age. In a study, panoramic dental radiographs from a Saudi Dental Hospital were analyzed using various CNN algorithms to estimate age based on 7 left lower mandibular teeth. Figure 2 represents a typical CNN architecture and its respective layers. It was revealed that the Xception model gave a better performance in the estimation of odontological age in comparison to the actual age. It attained a mean absolute error (MAE) of 1.4 years pertaining to the 6-11 age group and an exceptional precision proving that it can serve as a reliable tool for estimating dental age, even with a relatively smaller dataset [11], [18], [19]. The region around the molars, maxillary sinuses, and nasal septum also exhibits important information regarding the age of an individual. In a study, the researchers employed a collection of panoramic dental radiographs of the upper and lower jaw of individuals aged 5-25 years for predicting the age using the mentioned parameters. They employed a Bayesian CNN for this purpose. The architecture employed by the CNN model was Inception V3 which provides age estimation as well as quantification of uncertainty. The mean absolute error (MAE) varied significantly among age groups, with the lowest errors observed in the youngest group (MAE = 12.8) and the largest errors in young adults (MAE = 28.6). The initial results shown by the neural network were satisfactory but the accuracy has not yet reached a level required for application in real-case scenarios. It can be increased by applying multi-task learning and the use of saliency maps for the identification of potential new markers to estimate age using OPGs. In addition, the study highlights the importance of including quantitative uncertainty measures in legal contexts [10], [20]. Transfer learning models hold significant potential for age estimation using panoramic radiographs of the permanent dentition. In a study, various parameters like the mandibular angle, mandibular body, maxillary sinus, and the dentition were analyzed using ResNet, EfficientNet, VggNet, and DenseNet, and the results indicated that transfer learning models exhibited a good performance in estimating age of different age groups [11], [21]. Another study highlights 2 CNN-based methods – DANet and DASNet to estimate dental age using orthopantomograms of subjects aged 4.5 to 89.2 years. The findings showed that DASNet performed better than DANet in all parameters, exhibiting high accuracy in predicting the chronological age of subjects, especially younger individuals with developing dentition. It could detect even minute gender-related distinctions in facial features, which can be challenging for humans to discern. Furthermore, DASNet possessed the ability to process large volumes of images rapidly, making it more efficient than manual age prediction methods [10], [11], [12].

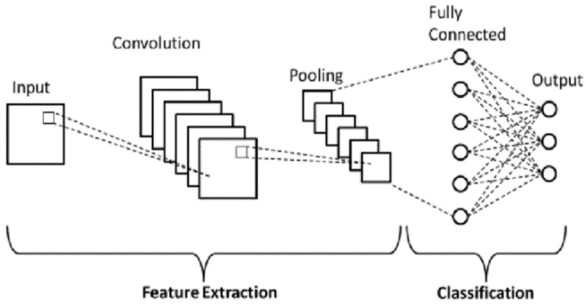

Figure 2. *Common architecture of a Convolutional Neural Network (CNN) comprising an input and output layer, as well as numerous hidden layers including a convolution layer, pool layer, and fully connected layer.*

The pelvis is also an important part of the human skeletal system in which various landmarks like the iliac crest, coccyx, pubic symphysis, ischial tuberosity, etc. are present. These landmarks can prove to be very useful in determining an individual's age by observing the ossification patterns. In a study, the scientists used a dataset comprising clinical pelvic X-ray images for examining the ossification of the ischial tuberosity and iliac crest to determine age. A Deep Convolutional Neural Network (DCNN) was employed for this purpose. A mean error value of 0.94 years was observed, demonstrating an improvement of 0.36 years over the current reference standard. In this study, the use of transfer learning from a CNN trained in advance on the ImageNet database was reported and a suitable accuracy was achieved for the input data [7], [14], [22].

Computed Tomography is also an important technique for age estimation, just like radiography. It is capable of providing useful insights into an individual's age. A recent study utilized a dataset of whole skull CT scans to estimate age through 3D-CNN, mainly focusing on the dense tissue layer regions. The findings indicated that the combination of CT and 3D-CNN can give an accurate and reliable determination of dental age [1], [17]. CBCT, a new variant of the traditional CT, is also widely used nowadays. It has been reported that this technique, when used with a combination of ANNs, can give highly accurate results for age determination. In a study, the researchers devised a novel method utilizing ANNs to estimate the dental age, focusing on the ratio of pulp-to-tooth in canines. CBCT images of canines were used as the dataset in this study. The proposed method showed high precision with a mean absolute error value of 4.12 years, making it a valuable tool to enhance the authenticity of the age determination process in forensic investigations [11], [23].

In recent years, MRI has gained a lot of popularity as a substitute for X-ray image-based age estimation methods. The development of automated MRI-based age determination methods depends on a variety of factors such as addressing the issue of ionizing radiation exposure, the need to introduce new staging systems specific to MRI, and the examiner's subjective influence. Generally, AI-based models such as RFs draw conclusions based on the features provided by the user whereas DCNNs automatically identify the important features. In a study, the researchers compared RFs and DCNNs in their ability to estimate age through regression and categorization of the dataset into minors and adults on the basis of bone ossification patterns. They used a dataset of hand/wrist MRI scans. To gather information about how the decision-making process is affected by different input information, three strategies were evaluated: using the entire hand image, a cropped picture showing the age-related bones, or a manual filter-based enhancement of the epiphyseal gap. DCNN achieved MAE and standard deviation of 0.20 ± 0.42 years using cropped images and RFs achieved MAE and standard deviation of 0.23 ± 0.45 years using enhanced images. These findings indicated that a high degree of accuracy is possessed by the two methods as compared to the previous MRI-based methods and the author's earlier research. The techniques were also used for 2D MRI scans and the results were found to be comparable to the advanced X-ray-based methods [7], [14], [24]. Other AI models like multiple linear regression have also demonstrated significant accuracy in predicting an individual's age from MRI scans of the left hand based on their gender as well as the measurement of carpals [1], [25].

Recently, the histomorphometric features of osseous and cartilaginous tissue aging have been used by some researchers for accurately classifying the age of individuals at death. The dataset utilized for this purpose was the results of morphometric analyses conducted on histological specimens of bone and cartilage tissue from deceased males. Various machine learning algorithms including KNN, logistic regression, SVM, SGD, Naïve Bayes, CatBoost, and RF were employed in the study, along with techniques for reducing dimensionality in a non-linear manner like uMAP and t-SNE, and for feature selection, recursive feature elimination was used. The machine learning techniques represented the entire dataset in an effective manner, revealing cluster structures within the low-dimensional feature space. In the identification of certain age groups, the accuracy reached as high as 90%, proving the high efficiency of these techniques in the age estimation process [26].

3. Skull Ancestry Estimation

Determination of the skull's ancestry provides valuable information to forensic anthropologists which can aid in the personal identification process to a great extent. It is also an important parameter just like age and sex estimation. In this respect, a study was conducted in which the concept of ANcestry Identification Network (ANINet) was introduced which aimed to enhance the precision and effectiveness in the process of skull ancestry estimation to help in individual identification. It performed much better as compared to the traditional networks and its accuracy ranged from 98.04% to 99.03%. It also eliminated the requirement for manual calibration and showed enhanced learning rates and estimation capabilities, thus making it an effective tool for skull ancestry estimation [11], [27].

4. Facial Reconstruction

Facial reconstruction holds significant importance in forensic investigations for establishing the identity of unknown individuals. Determination of mandibular morphology plays a crucial role in reconstructing the faces of individuals for their identification. Recently, a study was conducted that utilized a dataset of panoramic radiographs for the automatic characterization of mandible shape. The researchers used CNN for this purpose and focused mainly on the anatomical landmarks and semi-landmarks as well as a few descriptors. The proposed methodology included a shape model, a quantitative analysis of the shape of the mandible, and a visual depiction showcasing its variations. The results showed that this approach can prove to be very useful in forensic medicine case scenarios [11], [28].

Sphenoid hemisinuses are also integral to the facial reconstruction process. In a study, the researchers came up with the idea of automated sphenoid hemisinuses' reconstruction in 3D. The proposed methodology was tested on a dataset involving 85 computed tomography scans from 72 persons. They utilized a Fuzzy C-Means clustering algorithm for separating the sphenoid sinus and the adjacent bones. Furthermore, mathematical morphology techniques were applied to eliminate noise and enhance the segmentation mask. They employed a layered convolutional autoencoder incorporating dilated residuals for the extraction of complex shape-related features from the segmented mask. The resultant binary segmented masks were then projected into a compressed, lower-dimensional space to maintain semantic resemblance. This approach achieved 100% accuracy in the identification process [11], [29].

5. Personal Identification Using Dental Data

Teeth are considered to be the toughest part of the human body that can withstand even mass disasters e.g. an explosion. Due to this property, they are widely used for personal identification in cases where the person's body is almost completely damaged. Japan is making a lot of efforts in this direction. They have created AI systems that will identify deceased individuals in mass disaster cases by using panoramic dental radiographs, intraoral photographs as well as 3D data from intraoral scanners within dental records. This initiative originated from Japan's efforts to merge electronic dental data and medical records into a unified format, that will provide faster identification of disaster victims [1], [30].

Recently, various studies have been conducted using dental radiographs. One such study utilized a Faster Regions-based Convolutional Neural Network (R-CNN) and a Deep Neural Network (DNN) for identifying missing teeth, accompanied by a rule-based module for aligning the labels and refining the outcomes. The dataset comprised dental X-ray films. The findings of the study showed a high accuracy in tooth detection [11], [31], [32]. Another study utilized CNNs to match panoramic dental radiographs for personal identification. The main focus was on dental restorations, morphology of teeth, characteristics of periodontal tissue, specific teeth's presence or absence, pathology, and other morphological features. It attained an accuracy of 87.21% in correctly identifying subjects at the highest rank and a 95.34% accuracy within the top five ranks. The findings indicated that the CNNs are a reliable tool for individual identification from panoramic dental radiographs [11], [33]. In another research, the researchers proposed a methodology in which the model underwent training using images comprising tooth annotations extracted from panoramic dental radiographs of permanent dentition. The model showed a mean Intersection over Union (IoU) value of 0.877, indicating accurate segmentation of teeth. The model's accuracy was confirmed by visual evaluation and showed a close match to the ground truth annotations [11], [34].

6. Personal Identification Using Microbes

Microbes play a very important role in identifying unknown individuals as each person possesses a unique set of microorganisms. In a study, samples of microorganisms from the hands and possessions of volunteers were collected and further analyzed through the RF model. *Cutibacterium acnes* 16S rRNA genotype was integrated with profile data of skin microbiome and the model achieved an accuracy percentage value of 90 in the identification of individuals. Efforts have also been made to utilize microbial composition for the purpose of distinguishing between different tissues and body fluids. This approach can serve an important role in crime scene reconstruction. Some researchers used ANN and employed it on a vast dataset of 16S rRNA gene sequencing data pertaining oral, skin, and vaginal samples from the Human Microbiome Project (HMP). The main focus point here was the hypervariable regions of the 16S rRNA gene that helped in the accurate classification of the respective body sites [35], [36], [37

7. Injuries

In the field of forensic medicine, an injury can be defined as any breach in the anatomical continuity of the body tissues. There are various types of injuries encountered in medico-legal cases like abrasions, bruises, lacerations, burns, etc. Bone lesions also come under this category. Recently, some researchers tackled the challenge of accurate classification of osteolytic lesions in radiographs by addressing the lack of positive samples in the training dataset. They used a Cycle-consistent Generative Adversarial Network (Cycle GAN) which could generate osteolytic lesions on visuals free of any pathology. The generative task was framed as a visual-patch translation problem, specially customized for bones like the humerus, tibia, and femur. They also proved that their proposed methodology effectively alleviates the problem of class imbalance in tasks like binary classification related to bone lesion detection. Furthermore, it was illustrated that the training of improved classifiers can be facilitated by augmented training datasets that will lead to increased performance on a distinct test dataset.

In addition, the applicability of transfer learning was presented by using a generative model instructed on one anatomical region to another [14], [38].

Due to the progress and maturation of omics technologies, studies in the field of forensic medicine have transformed from singular experimental designs to incorporating mining, analysis of information, and mathematical modeling on the basis of high-throughput biological data. A research study in this domain introduced an innovative method to estimate wound age by merging biological omics data with AI algorithms. The researchers used transcriptomics data to determine time-related changes in gene expression after skeletal muscle injury. Five machine-learning models including RF, Logistic Regression, Neural Network, SVM, and Gradient Boosting Decision tree were devised to estimate wound age using the expression level corresponding to 50 gene indicators. To compare the performance of models, evaluation metrics like prediction, accuracy, area under the curve, and recall were used. It was noted that the RF model's performance was most consistent. This research implied a substantial stride forward in the accuracy and fairness of wound age estimation [39].

8. Examination Of Diatoms

Diatoms are microscopic algae that have been used in drowning investigations to determine the cause of death since traditional times. Figure 3 represents the appearance of some common diatom species [40].

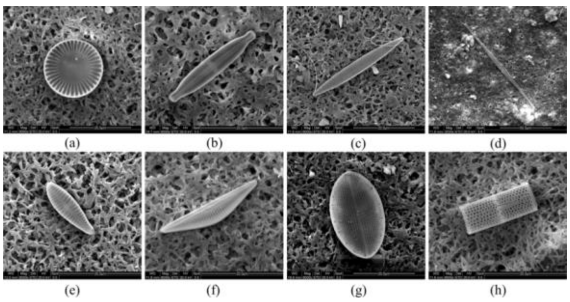

Figure 3. *Representation of some diatoms: (a) Cyclotella; (b) Navicula; (c) Nitzschia; (d) Synedra; (e) Gomphonema; (f) Cymbella; (g) Cocconeis; (h) Melosira*

Recently, AI algorithms like CNN have been employed to automatically detect diatoms from digital images of whole-slides through transfer learning and data augmentation methods. CNN performed much better than human experts as it took comparatively less time to identify more diatoms [1], [37], [41].

9. Postmortem Imaging

Post-mortem computed tomography (PMCT) is a very useful technique used in forensic pathology that offers visualization of patterns of injuries, anatomical structures, and the positioning of foreign objects in a detailed manner before dissection. Moreover, contemporary AI technologies are incorporated for the purpose of screening and computer-aided diagnostics. In a study, CNN was employed on a dataset of PMCT visuals of the cross-sectional view of the head at the frontal sinus level. Specific features that correlated with fatal head injuries like epidural hemorrhages, subarachnoid hemorrhages, skull fractures, brain contusions, subdural hemorrhages and parenchymal hemorrhages were taken into account. Tasks like image classification and interpretation were performed by the respective model in a precise way. The results of the study proved that AI can be employed as a valuable screening tool in post-mortem imaging. It can also be used as a substitute for traditional autopsy procedures. Apart from two-dimensional images, computed tomography data can also offer three-dimensional images that necessitate volumetric segmentation and analysis. These 3D visuals can help in detecting fractures as well as identification of medical conditions like skin anomalies and cancer in postmortem examinations [1], [42].

In another study based on PMCT scans, the researchers employed Residual Networks (ResNets), Hybrid Convolutional Autoencoder (HCAE), and KNN for locating and classifying orthopedic implants within the femur across a vast dataset of whole-body PMCT scans. At the localization stage, the system achieved high Dice scores (0.98, 0.96, and 0.99) and mean absolute errors (4.2, 7.1, and 3.2 mm) in the sagittal, coronal, and axial views, respectively. Regarding classification, the test cases were appropriately labeled with an accuracy percentage of more than 97, and the recall rate for two of the classes was 1.00, and for the other two classes, it was 0.82 and 0.65. Although the results can be considered very good, the study emphasizes that this area of research remains largely undiscovered [14], [43].

10. Post-Mortem Interval Estimation

Estimation of time since death is a very crucial aspect of forensic medicine that can assist in reconstructing the events in criminal investigations. There are various biomarkers present in the blood that can be used for PMI estimation. The body starts decomposing after death and this results in a change in biomarker concentrations relative to the duration of time passed. In a study, an AI device was introduced to estimate PMI by analyzing the profile of various biomarkers present in the blood samples obtained from the deceased person's femoral vein. These blood biomarkers include Lactate dehydrogenase, Aspartate aminotransferase, triglycerides, and cholesterol. The proposed device could also measure the blood pH. For estimating PMI, the interpretation and comparison of the device's output to various databases can be done. The authors recommended that decisions should be made regarding the usage of this device only after proper evaluation by concerned institutions [1], [44], [45].

The sequences of microbial communities are also useful in determining the PMI. In a study, the researchers integrated microbial community characterization and microbiome sequencing from various organs (such as the heart, brain, and cecum) with AI algorithms including ANN, RF, and SVM. The main focus was to analyze the microbial progression pattern throughout the decomposition process of mice corpse. Significant differences were found in the microbial communities between the time of death and the stages of decomposition. The most relevant species in the decomposition process were *Lactobacillus reuteri, Anaerosalibacter bizertensis, Enterococcus faecalis,* etc. The most effective combination was the ANN integrated with post-mortem microbial data retrieved from the cecum. This model showed an accurate and reliable estimation of PMI [46], [47].

Recently, Near Infrared Spectroscopy has also proved to be a valuable technique for accurate estimation of PMI. A study utilized the Near Infrared (NIR) spectra of human bone samples spanning from 1 day to 2000 years old for this purpose. The AI algorithm employed here was ANN and the main focus was on the diaphysis of the femur. The algorithm effectively differentiated between forensic and archaeological bone specimens. It provided a highly accurate classification for various PMI intervals: 0–2 weeks (0.90), 2 weeks–6 months (0.94), 6 months–1 year (0.94), 1 year–10 years (0.93), and >100 years (1.00). Moreover, the model achieved 100% accurate results in determining the PMI of archaeological bone specimens, highlighting its remarkable performance [48].

11. Cause Of Death Determination

AI can be used for examining both the internal and external characteristics of a deceased person, as well as the statements given by family members for determining the cause of death. AI autopsy imaging techniques and natural language processing algorithms are used for this purpose [1].

12. DNA Databases

DNA is unique for every individual and this uniqueness makes it one of the most reliable pieces of evidence that can be used for accurate human identification. There are several DNA databases used in different countries across the world that are based on AI for their functioning. One such AI tool is the Combined DNA Index System (CODIS), that is used by the Federal Bureau of Investigation (FBI) in US to match crime-scene DNA with known DNA samples. The United Kingdom also has its own national database called the National DNA Database (NDNAD) which is large-scale as compared to CODIS and includes familial screening. In Malaysia, the Forensic DNA Database Malaysia (FDDM) is used for DNA analysis in forensic investigations. This database uses AI algorithms for comparison of DNA recovered from the crime scene with profiles stored in the system. This allows law enforcement agencies to carry out proper identification of potential suspects [2].

13. Examination Of Stains

In cases like sexual assaults, AI microscopy imaging techniques can help in visualizing sperm cells in a highly accurate manner. In a study, the researchers used CNN which enables automatic analysis of images for identifying substances and objects within the visuals. This approach is not only limited to the identification of sperm stains. Fingerprints present on surfaces or blood spatter patterns on clothing can also be identified using it [45], [49].

14. Toxicological Analysis

AI is also being widely used in performing the toxicological analysis of biological specimens. For this purpose, the AI machine is equipped with a set of algorithms that allow it to carry out sample analysis with a high degree of accuracy and more quickly in comparison to the traditional analytical methods. In addition, the integration of AI with robotics can be done for the automation of several tasks in toxicological testing such as the collection and transportation of samples. There are numerous benefits of incorporating AI into the work of forensic toxicologists like increased efficiency, greater accuracy, diminished costs as well as the probability of bringing new forms of toxicological testing [45]

Table 1. Detailed studies depicting some of the applications of AI in the field of forensic medicine

Sr. No.	Forensic medicine application	AI Method/Model /Technique/Algorithm/Architecture employed	Dataset/ Sample used	Main focus	Accuracy percentage	Other specific performance metrics	References
1.	**Sex Estimation**	Discriminant analysis, Artificial Neural Network (ANN), Stochastic Gradient Descent (SGD), K-Nearest Neighbour (KNN), Naïve Bayes, Logistic Regression	Panoramic dental radiographs	Anatomical points (13 measurements of the mandible)	Discriminant analysis gave >70% and ML techniques gave 95%	Intra-class coefficient (ICC): above 0.90, Coefficient of variation (CV): below 5%.	[6], [7]
		Discriminant Analysis, Logistic Regression, Artificial Neural Network (ANN)	Panoramic dental radiographs	Mandibular morphometric parameters	69.1%, 69.9, 75% respectively	Intra-class correlation coefficient values ranged from 0.84 to 1	[9], [10], [11]

		Convolutional Neural Network (CNN)-based Dental Age and Sex Net (DASNet)	Orthopantomogram (OPG) images	Sex-specific features at different scales	NA	Median Error: 0.12 years, Median Absolute Error: 1.48 years, Accuracy value: 0.854	[10], [11], [12]
		Backpropagation Neural Network (BPNN)	Whole skull CT scans of an ethnic group(Uighur) from northern China	6 skull measurements: apical sagittal chord, apical sagittal arc, occipital sagittal chord, occipital sagittal arc, cranial sagittal chord, and cranial sagittal arc	Training Accuracy: 97.232%, Testing Accuracy: 96.764%.	Mean squared error (MSE) in the training stage: 0.01, Mean Squared Error (MSE) in the testing stage: 1.016	[13], [14]
		3D morphometrics and virtual models	Cranial CT images	Roundness of the frontal bone	72.8%	Decision threshold: 41.076%	[11], [15]

			of Czech adults				
		Convolutional Neural Network (CNN)	Skull images reconstructed from CT scans	Sexually dimorphic ectocranial features	95%	Matthews correlation coefficient (MCC): 0.9	[11], [14], [16]
		3 Dimensional-Convolutional Neural Network (3D-CNN)	Full-head 3D CBCT scans	Thresholded hard and soft tissues	NA	NA	[1], [17]
2.	**Age Estimation**	Convolutional Neural Networks (CNNs)	Dental panoramic radiographs	7 left lower mandibular teeth	NA	Xception model performed the best, achieving MAE of 1.417 for the 6–11 age group	[11], [18]
		Bayesian Convolutional Neural Network (CNN)	Panoramic dental radiographs of the upper and lower jaw	The region around maxillary sinus, molars and nasal septum	NA	concordance correlation coefficient(ccc) = 0.91	[10], [20]
		Residual Networks (ResNet),	Panoramic radiogra	Mandibular angle, mandibular	NA	The best-performing model was	[11], [21]

		Efficient Neural Networks (EfficientNet), Visual Geometry Group Networks (VggNet), Densely connected Convolutional Networks (DenseNet)	phs of permanent dentition	body, dentition, and maxillary sinus		EfficientNet-B5, with an MAE and RMSE of 2.83 and 4.59 respectively	
		Dental Age Net (DANet) and Dental Age and Sex Net (DASNet)	Orthopantomogram (OPG) images of teeth	Image features at different scales, sex-related characteristics at intermediate points	NA	DASNet performed better than DANet, achieving a median error of 0.12 years, a median absolute error (MAE) of 1.48 years, and an accuracy of 0.854	[10], [11], [12]
		3D-Convolutional Neural Network (3D-CNN)	Whole skull CT scans	Dense tissue layer regions	NA	NA	[1], [17]

		Artificial Neural Network (ANN)	CBCT images of human canines	The ratio of pulp-to-tooth in canines	NA	Root Mean Square Error (RMSE): 4.40 years, Mean Absolute Error (MAE): 4.12 years	[11], [23]
		Deep Convolutional Neural Network (DCNN)	Clinical pelvic radiographs	Ossification of iliac crest and ischial tuberosity	NA	Root Mean Square Error (RMSE): 1.30 years, Mean Absolute Error (MAE): 0.94 years, correlation coefficient (R^2): 0.92883	[7], [14], [22]
		Deep Convolutional Neural Network (DCNN), Random Forest (RF)	3D MRI scans of left hand	Bone ossification patterns	NA	Mean Absolute Error (MAE) for i)Subjects aged ≤ 18 years: 0.37 ± 0.51 years,	[7], [14], [24]

						ii)Full dataset: 0.20 ± 0.42 years	
		Multiple linear regression	MRI of the left hand	The ratio between the ossification nucleus area and the growth surface of each carpal bone	NA	Median of the residuals (observed age minus predicted age): -0.025 years, Interquartile range (IQR): 0.19 years	[1], [25]
		Support Vector Machine (SVM), K-nearest neighbor (KNN), CatBoost, Logistic regression, Stochastic Gradient Descent (SGD), Random Forest (RF), Naïve Bayes, Non-linear techniques for	Results from morphometric studies of histological specimens of bone and cartilage tissue from deceased males	Histomorphometric characteristics of bone and cartilaginous tissue aging	90%	NA	[26]

		reducing dimensionality, and feature elimination through recursion					
3.	**Personal identification using dental data**	Image analysis	Intraoral photographs, 3D data from intraoral scanners, dental panoramic radiographs	Dental findings	NA	NA	[1], [30]
		Deep Neural Network (DNN), Faster Regions-based Convolutional Neural Network (R-CNN)	Dental X-ray films	Teeth numbering and their respective positions	NA	Recall and precision exceed 90%, Mean value of the Intersection over union (IOU) between detected boxes and ground Truths: 91%	[11], [31], [32]

		Convolutional Neural Network (CNN)	Panoramic dental X-ray images	Dental restorations, morphology of teeth, characteristics of periodontal tissue, specific teeth's presence or absence, pathology, and other morphological features	Rank-1 accuracy: 87.21% and Rank-5 accuracy: 95.34%	NA	[11], [33]
		Deep Regions-based Convolutional Neural Network (R-CNN)	Panoramic dental X-ray images of permanent dentition	Tooth structures	NA	Precision: 0.858, F1-score: 0.875, Mean IoU: 0.877, Recall: 0.893,	[11], [34]

4.	**Detection and examination of injuries**	Cycle-consistent Generative Adversarial Network (CycleGAN)	X-ray images of hand and leg bones	Bone lesions	NA	Highest validation set AUC $t_{humerus}$: 0.9, t_{femur}: 0.95, t_{tibia}: 0.9	[14], [38]
		Logistic regression, Random Forest (RF), Gradient boosting decision tree, Support Vector Machine (SVM), neural network	Transcriptomics data, 64 SD-rats' RNA	Expression levels of 50 gene indicators	NA	NA	[39]

Challenges and Limitations:

Implementation of artificial intelligence in the field of forensic medicine faces a lot of challenges as well as limitations regarding its applicability in real-time case scenarios. The major issues are as follows:

1. Training The Machines

AI models require an enormous amount of data to give an accurate output. It should be of high quality so that the AI machine can be trained on it to give highly reliable results. These AI models represent the entire population and can bring variations in the results if proper training on diverse datasets is not provided. Forensic medicine experts initially need to annotate images and documents manually with key findings, conclusions, and supplementary details for machine processing which requires significant effort from them [11], [45].

2. Compliance and Standards

AI is a strong tool that helps in getting things done faster with a high accuracy. However, its execution prompts ethical inquiries and poses challenges to current regulatory frameworks. Some researchers think that too much dependency on AI might stop us from using our own judgement that we have been doing since traditional times [45].

3. Reliability And Accuracy

The relationship between forensic medicine professionals and their clients and stakeholders must be trustworthy. It is a matter of great concern whether the judiciary, law enforcement agencies, and the general public will trust the findings given by the AI machines. For this reason, forensic experts are required to give explanations to their clients regarding the accuracy and trustworthiness of the opinions given by AI [45].

4. Human Interaction

AI cannot undermine human interaction and expertise despite its functioning as an automated machine. Human effort is important for processing every data fed into the

system. Therefore, significant cooperation from forensic experts is required for initially training the machine with ongoing updates to maintain its effectiveness [45].

5. Interoperability

Diverse AI tools may lack interoperability which can potentially lead to the creation of isolated data silos. This could lead to duplicated efforts as information becomes scattered and inaccessible across various systems [45].

6. Medicolegal Implications

As per the legal system, every documentary evidence should be verbally attested by an expert. Therefore, the important concern in forensic medicine is whether AI-generated opinions will be considered admissible as a proof in the court of law [45].

7. The Situation in Developing Nations

Countries in development stages, such as India, harbor a substantial segment of population that is out of the reach of advanced healthcare facilities. Due to this, policymakers face a lot of challenges in establishing cutting-edge infrastructure in the domain of forensic medicine [45].

8. Errors And Bias-Related Issues

The AI models have been devised to be impartial and data-driven. But the quality of data can affect their performance e.g. if inaccuracies or prejudices exist within the training data, they might reflect in the functioning of the model. Furthermore, insufficient testing and validation of the AI model across varied datasets may result in poor performance when employed in real-world situations [11], [50].

9. Concerns About Admissibility

AI-generated reports can be very difficult to understand because there is a lot of math happening behind the scenes. In addition, if the data used by forensic medicine experts is wrong or incomplete or if any cyberattack is involved, it can produce unfair results. Moreover, AI systems learn and change over time, making it tough to hold programmers responsible if something goes wrong. Due to all these factors, judges and lawyers face a lot of challenges in deciding whether these reports can be trusted for things like accuracy, reliability, clarity, and fairness [37], [41].

10. Specialized Training for Experts

Forensic medicine experts need special training for using AI models so that they can understand and interpret the results. However, some experts might hesitate to incorporate AI technologies in their daily work because of concerns regarding biases in the technology [1].

Conclusion

Artificial intelligence has transformed the way of working of professionals in the domain of forensic medicine to a great extent. The incorporation of various AI techniques into traditional human-based procedures has revolutionized this field by enhancing accuracy, making analysis much faster than ever, reducing human bias, increasing efficiency, and so on. AI is reaching almost every sub-domain of forensic medicine such as forensic odontology, forensic anthropology, forensic radiology, forensic pathology, forensic nursing, and many others. Despite all these benefits, limitations and challenges like medico-legal implications, bias-related issues, interoperability, admissibility concerns, etc. must be meticulously handled to ensure the conscientious and ethical deployment of AI in forensic medicine. As AI continues to evolve, its integration into forensic medicine practices holds great potential to innovate this field, ultimately leading to improved forensic investigations, enhanced judicial outcomes, and a safer society.

Ethical Clearance: Not required

Conflict of Interest: None to Declare

References

1. Pathirannahalage, I., Vidanapathirana, M., and Subashinghe, A. (2022). Artificial Intelligence for Forensic Medicine. *Medico-Legal Journal of Sri Lanka*. 10(2), 17. doi: 10.4038/mljsl.v10i2.7469.

2. Noor Hazfalinda Hamzah, A., Xuan, S.L., Francesca Gabriel, G., Osman, K., and Mahiza Isa, N. (2022). Artificial Intelligence in Forensic Science: Current Applications and Future Direction. *Buletin SK*. 6(2), 39-46. Available from: http://myjms.mohe.gov.my/index.php/bsk

3. Kotsyubynska, Y.Z., Voloshynovych, V.M., Solodjuk, Y.I., Liampel, V.I., and Fentsyk, V.L. (2023). ARTIFICIAL INTELLIGENCE – APPLICATION IN FORENSIC

MEDICINE. *Clinical and Preventive Medicine*. 2023(6), 54–60. doi: 10.31612/2616-4868.6.2023.06.

4. Gupta, S., Sharma, M.V., and Johri, P. (2020). ARTIFICIAL INTELLIGENCE IN FORENSIC SCIENCE. *International Research Journal of Engineering and Technology* [Internet]. 7(5), 7181-7184. Available from: www.irjet.net

5. Singh Sankhla, M., Kumar, R., and Jadhav, E.B. (2020). Artificial Intelligence: Advancing Automation in Forensic Science & Criminal Investigation. *Journal of Seybold Report.* 15(8), 2064-2075. Available from: https://www.researchgate.net/publication/343826071

6. Ortiz, A.G., Costa, C., Silva, R.H.A., Biazevic, M.G.H., and Michel-Crosato, E. (2020). Sex estimation: Anatomical references on panoramic radiographs using Machine Learning. *Forensic Imaging*. 20. doi: 10.1016/j.fri.2020.200356.

7. Peña-Solórzano, C.A., Albrecht, D.W., Bassed, R.B., Burke, M.D., and Dimmock, M.R. (2020). Findings from machine learning in clinical medical imaging applications – Lessons for translation to the forensic setting. *Forensic Science International*. Elsevier Ireland Ltd. 316. doi: 10.1016/j.forsciint.2020.110538.

8. Shimabukuro, H., Mao, Y., and Tan, J. (2020). Beyond power spectrum I: recovering HII bubble size distribution from 21cm power spectrum with artificial neural network Beyond the power spectrum-I: recovering H II bubble size distribution from 21 cm power spectrum with artificial neural networks [Internet]. *MNRAS*. 1-12. Available from: http://gmrt.ncra.tifr.res.in

9. Patil, V., Vineetha, R., Vatsa, S., Shetty, D.K., Raju, A., Naik, N., et al. (2020). Artificial neural network for gender determination using mandibular morphometric parameters: A comparative retrospective study. *Cogent Eng*. 7(1). doi: 10.1080/23311916.2020.1723783.

10. Khanagar, S.B., Vishwanathaiah, S., Naik, S., A. Al-Kheraif, A., Devang Divakar, D., Sarode, S.C., et al. (2021). Application and performance of artificial intelligence technology in forensic odontology – A systematic review. *Legal Medicine*. Elsevier B.V. 48. doi: 10.1016/j.legalmed.2020.101826.

11. Zain-Alabdeen, E., and Felemban, D. (2023). Artificial intelligence and skull imaging advancements in forensic identification. *Saudi J Health Sci*. 12(3), 171. doi: 10.4103/sjhs.sjhs_124_23.

12. Vila-Blanco, N., Carreira, M.J., Varas-Quintana, P., Balsa-Castro, C., and Tomas, I. (2020). Deep Neural Networks for Chronological Age Estimation from OPG Images. *IEEE Trans Med Imaging*. 39(7), 2374–84. doi: 10.1109/TMI.2020.2968765.

13. Yang, W., Liu, X., Wang, K., Hu, J., Geng, G., and Feng, J. (2019). Sex determination of three-dimensional skull based on improved backpropagation neural network. *Comput Math Methods Med*. 2019. doi: 10.1155/2019/9163547.

14. Mesejo, P., Martos, R., Ibáñez, Ó., Novo, J., Ortega, M. (2020). A Survey on artificial intelligence techniques for biomedical image analysis in skeleton-based forensic human identification. *Applied Sciences (Switzerland)*. MDPI AG; 10(14). doi: 10.3390/app10144703.

15. Čechová, M., Dupej, J., Brůžek, J., Bejdová, Š., and Velemínská, J. (2021). A test of the Bulut et al. (2016) landmark-free method of quantifying sex differences in frontal bone roundness in a contemporary Czech sample. *J Forensic Sci*. 66(2), 694–9. doi: 10.1111/1556-4029.14603.

16. Bewes, J., Low, A., Morphett, A., Pate, F.D., and Henneberg, M. (2019). Artificial intelligence for sex determination of skeletal remains: Application of a deep learning artificial neural network to human skulls. *J Forensic Leg Med*. 62, 40–3. doi: 10.1016/j.jflm.2019.01.004.

17. Thurzo, A., Kosnáčová, H.S., Kurilová, V., Kosmeľ, S., Beňuš, R., Moravanský, N., et al. (2021). Use of advanced artificial intelligence in forensic medicine, forensic anthropology and clinical anatomy. *Healthcare (Switzerland).* 9(11). doi: 10.3390/healthcare9111545.

18. Aljameel, S.S., Althumairy, L., Albassam, B., Alsheikh, G., Albluwi, L., Althukair, R., et al. (2023). Predictive Artificial Intelligence Model for Detecting Dental Age Using Panoramic Radiograph Images. *Big Data and Cognitive Computing*. 7(1). doi: 10.3390/bdcc7010008.

19. Liu, G., Zhang, Z., Jiang, R., Crookes, D., and Chazot, P. (2022). EEG-based Deep Emotional Diagnosis: A Comparative Study. *In: Recent Advances in AI-enabled Automated Medical Diagnosis. CRC Press*. 317–28. doi: 10.1201/9781003176121-20.

20. De Back, W., Seurig, S., Wagner, S., Marré, B., Roeder, I., and Scherf, N. Forensic age estimation with Bayesian convolutional neural networks based on panoramic dental X-ray imaging. Accessed: Jun. 01, 2024. [Online]. Available: https://pure.mpg.de/rest/items/item_3166969/component/file_3166970/content

21. Mu, C.C., and Li, G. (2022). Age Estimation using Panoramic Radiographs by Transfer Learning. *Chin J Dent Res*. 25(2), 119–24. doi: 10.3290/j.cjdr.b3086341.

22. Li, Y., Huang, Z., Dong, X., Liang, W., Xue, H., Zhang, L., et al. (2018). Forensic age estimation for pelvic X-ray images using deep learning. *Eur Radiol.* 29(5), 2322–9. doi: https://doi.org/10.1007/s00330-018-5791-6.

23. Farhadian, M., Salemi, F., Saati, S., and Nafisi, N. (2019). Dental age estimation using the pulp-to-tooth ratio in canines by neural networks. *Imaging Sci Dent.* 49(1), 19–26. doi: 10.5624/isd.2019.49.1.19.

24. Štern, D., Payer, C., and Urschler, M. (2019). Automated age estimation from MRI volumes of the hand. *Med Image Anal.* 58. doi: 10.1016/j.media.2019.101538.

25. Scendoni, R., Cingolani, M., Giovagnoni, A., Fogante, M., Fedeli, P., Pigolkin, Y.I., et al. (2020). Analysis of carpal bones on MR images for age estimation: First results of a new forensic approach. *Forensic Sci Int.* 313. doi: 10.1016/j.forsciint.2020.110341.

26. Zolotenkova, G. V., Rogachev, A.I., Pigolkin, Y.I., Edelev, I.S., Borshchevskaya, V.N., and Cameriere, R. (2022). Age Classification in Forensic Medicine Using Machine Learning Techniques. *Sovremennye Tehnologii v Medicine*. 14(1), 15–24. doi: 10.17691/stm2022.14.1.02.

27. Pengyue, L., Siyuan, X., Yi, J., Wen, Y., Xiaoning, L., Guohua, G., et al. ANINet: a deep neural network for skull ancestry estimation. *BMC Bioinformatics*. 22(1). doi: 10.1186/s12859-021-04444-6.

28. Vila-Blanco, N., Varas-Quintana, P., Aneiros-Ardao, Á., Tomás, I., and Carreira, M.J. (2021). Automated description of the mandible shape by deep learning. *Int J Comput Assist Radiol Surg.* 16(12), 2215–24. doi: 10.1007/s11548-021-02474-2.

29. Souadih, K., Belaid, A., Ben Salem, D., and Conze, P.H. (2020). Automatic forensic identification using 3D sphenoid sinus segmentation and deep characterization. *Med Biol Eng Comput.* 58(2), 291–306. doi: 10.1007/s11517-019-02050-6.

30. H. T. (2019). Personal Identification From Dental Findings Using AI And Image Analysis Against Great Disaster In Japan. *Journal of Forensic, Legal & Investigative Sciences* [Internet]. 5(3), 1–4. doi: 10.24966/FLIS-733X/100041. Available from: http://www.heraldopenaccess.us/openaccess/personal-identification-from-dental-findings-using-ai-and-image-analysis-against-great-disaster-in-japan

31. Chen, H., Zhang, K., Lyu, P., Li, H., Zhang, L., Wu, J., et al. (2019). A deep learning approach to automatic teeth detection and numbering based on object detection in dental periapical films. *Sci Rep.* 9(1). doi: 10.1038/s41598-019-40414-y.

32. Görürgöz, C., Orhan, K., Bayrakdar, I.S., Çelik, Ö., Bilgir, E., Odabaş, A., et al. (2022). Performance of a convolutional neural network algorithm for tooth detection and numbering on periapical radiographs. *Dentomaxillofacial Radiology*. 51(3). doi: 10.1259/dmfr.20210246.

33. Lai, Y., Fan, F., Wu, Q., Ke, W., Liao, P., Deng, Z., et al. (2021). LCANet: Learnable Connected Attention Network for Human Identification Using Dental Images. *IEEE Trans Med Imaging.* 40(3), 905–15. doi: 10.1109/TMI.2020.3041452.

34. Lee, J.H., Han, S.S., Kim, Y.H., Lee, C., and Kim, I. (2020). Application of a fully deep convolutional neural network to the automation of tooth segmentation on panoramic radiographs. *Oral Surg Oral Med Oral Pathol Oral Radiol.* 129(6), 635–42. doi: 10.1016/j.oooo.2019.11.007.

35. Yang, J., Tsukimi, T., Yoshikawa, M., Suzuki, K., Takeda, T., Tomita, M., et al. (2019). Cutibacterium acnes (Propionibacterium acnes) 16S rRNA Genotyping of Microbial Samples from Possessions Contributes to Owner Identification. *mSystems.* 4(6). doi: 10.1128/msystems.00594-19.

36. Díez López, C. Forensic Microbiome: Novel applications of the human microbiome in forensic science. Available: thesis-Diez-Lopez.pdf (eur.nl)

37. Mishra, A., Khan, S., Das, A., and Das, B.C. (2023). Evolution of Diagnostic and Forensic Microbiology in the Era of Artificial Intelligence. *Cureus.* 15(9). doi: 10.7759/cureus.45738.

38. Gupta, A., Venkatesh, S.A., and Ledig, C.A. (2019). Generative Image Translation for Data Augmentation of Bone Lesion Pathology. *Proceedings of The 2nd International Conference on Medical Imaging with Deep Learning*. 102, 225-235.

39. Ren, K., Li, N., Liang, X., Wang, L., Li, J., and Sun, J. (2020). Investigating the new orientation of wound age estimation in forensic medicine based on biological omics data combined with artificial intelligence algorithms. *In: ACM International Conference Proceeding Series. Association for Computing Machinery*. p. 54–9. doi: 10.1145/3433996.3434007.

40. Deng, J., Guo, W., Zhao, Y., Liu, J., Lai, R., Gu, G., et al. (2021). Identification of diatom taxonomy by a combination of region-based full convolutional network, online hard example mining, and shape priors of diatoms. *Int J Legal Med.* 135(6), 2519–30. doi: 10.1007/s00414-021-02664-2.

41. Zhou, Y., Zhang, J., Huang, J., Deng, K., Zhang, J., Qin, Z., et al. (2019). Digital whole-slide image analysis for automated diatom test in forensic cases of drowning using a convolutional neural network algorithm. *Forensic Sci Int.* 302. doi: 10.1016/j.forsciint.2019.109922.

42. Garland, J., Ondruschka, B., Stables, S., Morrow, P., Kesha, K., Glenn, C., et al. (2020). Identifying Fatal Head Injuries on Postmortem Computed Tomography Using Convolutional Neural Network/Deep Learning: A Feasibility Study. *J Forensic Sci.* 65(6), 2019–22. doi: 10.1111/1556-4029.14502.

43. Peña-Solórzano, C.A., Albrecht, D.W., Bassed, R.B., Gillam, J., Harris, P.C., and Dimmock, M.R. (2020). Semi-supervised labelling of the femur in a whole-body post-mortem CT database using deep learning. *Comput Biol Med*. 122. doi: 10.1016/j.compbiomed.2020.103797.

44. Hachem, M. and Sharma, B.K. (2019). Artificial Intelligence in Prediction of PostMortem Interval (PMI) Through Blood Biomarkers in Forensic Examination–A Concept. *2019 Amity International Conference on Artificial Intelligence (AICAI), Dubai, United Arab Emirates*. pp. 255-258. doi: 10.1109/AICAI.2019.8701416.

45. Wankhade, T.D., Ingale, S.W., Mohite, P.M., and Bankar, N.J. (2022). Artificial Intelligence in Forensic Medicine and Toxicology: The Future of Forensic Medicine. *Cureus.* 14(8). doi: 10.7759/cureus.28376.

46. Liu, R., Gu, Y., Shen, M., Li, H., Zhang, K., Wang, Q., et al. (2020). Predicting postmortem interval based on microbial community sequences and machine learning algorithms. *Environ Microbiol*. 22(6), 2273–91. doi: 10.1111/1462-2920.15000.

47. Khakare, R., and Fatangare, S. (2020). Survey on Prediction of Post Mortem Interval using Artificial Intelligence in Forensic Examination. *International Research Journal of Engineering and Technology* [Internet]. 7(5), 5760-4. Available from: www.irjet.net

48. Schmidt, V.M., Zelger, P., Wöss, C., Huck, C.W., Arora, R., Bechtel, E., et al. (2022). Post-Mortem Interval of Human Skeletal Remains Estimated with Handheld NIR Spectrometry. *Biology (Basel)*. 11(7). doi: 10.3390/biology11071020.

49. Golomingi, R., Haas, C., Dobay, A., Kottner, S., and Ebert, L. (2022). Sperm hunting on optical microscope slides for forensic analysis with deep convolutional networks – a feasibility study. *Forensic Sci Int Genet.* 56. doi: 10.1016/j.fsigen.2021.102602.

50. Lorch, B., Scheler, N., and Riess, C. (2022). Compliance Challenges in Forensic Image Analysis Under the Artificial Intelligence Act. *30th European Signal Processing Conference (EUSIPCO), Belgrade, Serbia*. pp. 613-617. doi: 10.23919/EUSIPCO55093.2022.9909723.