Anthropology and Morphology-Based Facial Image Analysis to Support Criminal Investigation in Forensics

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Abstract: Identification of humans is an extremely important topic in today's society, particularly in the context of medical and legal matters. To correctly identify a person for legal purposes, it is necessary to describe, compare, and accurately attribute essential biological characteristics. As a direct result of this, each new technological advancement developed in this sector can add to the growing demand for precise and reliable instruments to establish and verify human identification. Even though it has been around for a very long time, forensic anthropology has reached significant advancement universally in the past thirty years. It is necessary to keep track of all of these advancements and evaluate the patterns at regular intervals. In addition, it is essential to determine the study topics that will be essential in the coming years. This special issue's objective is to take a closer look at some of the studies conducted within the 21st century in the hopes of spotting emerging patterns. The paper analyses a number of studies focused on the study of face characteristics and identification methods, such as facial profile estimation and skull-photo superimposition. Estimation of age (based on skull thickness and the fetus), sex (based on the supranasal area, arm, and leg bones), and height (based on the arm bones) have all been studied through the analysis of separate articles in this paper. Further, with the onset of increasing criminal activities, identifying criminals through forensics has also become of great importance. This paper studies and analyses various identification methods by the application of anthropology and morphology on forensics with the help of Artificial Intelligence mechanisms.

Keywords: Forensic sciences, Facial Structure, Morphological analysis, Computer Vision, Artificial Intelligence

Introduction

The term "forensic sciences" refers to a group of disciplines that share the goal of "materializing the proof under lawful reasons through a scientific methodology." This ambition is what gives the forensic sciences its name. In this respect, any scientific discipline can be considered "forensic" when it is used in the legal system [1]. Identifying the departed is a crucial stage in nearly every run-through linked to resolving a person's death. This includes legal measures relating to a person's demise, whether they be felonious (such as inquiries of assassination, mistreatment, or torture) or civil (such as lawsuits over wrongful deaths) (e.g., inheritance, marriage, or child custody). The family's mental health depends on the identity of the departed person just as much as it does on the physical health of the family. There is a growing body of research that refers to "ambiguous loss" and the considerable mental health problems that are caused by the uncertainty as well as the difficulty to grieve and find peace until the situation of the person of interest is known [2] [3]. This research is a component of a wider body of research that refers to "ambiguous loss." [4]

For the same, facial recognition is a significant factor in determining the identity of a person. The human face is an intrinsic component that not only reflects details of a person's physical profile, like age, sex, and ethnic background but also reflects the person's well-being and emotional health. The human face can tell much about a person by looking at them. In forensic identification, therefore, the features and physical traits of the face play a significant role. As visual evidence, facial captures from closed-circuit video (CCTV) are recognized and admissible.

Closed-circuit television has therefore also been a very helpful tool in identifying and detaining those involved in any and all forms of illegal activity. The process of identifying a suspect's face through the use of forensic facial analysis [5] [6] involves comparing CCTV photos of an offender that were collected at the scene of a crime with photographs of suspects that were taken while they were in jail. On the other hand, CCTV images are frequently grainy, have a low chromatic dispersion, or show people's faces in inadequate lighting and at strange angles [7]. This report aims to describe various methods of facial analysis and investigate how negative factors that influence bad quality CCTV images impact a forensic expert's conclusion.

Another helpful tool in facial recognition for forensics is morphology. Morphology is a subjective process based on the observation and comparison of the form, exterior, presence, and position of facial features [8]. This process aims to define apparent similarities and differences between subjects depicted in the various images used for the comparison[9]. These characteristics include both global (i.e. the entire face) and local (i.e., anatomical structures, such as eyes, nose, and mouth, and their components, such as eyeball prominence, nasal root, nostrils, and philtrum) characteristics, as well as distinguishing characteristic facial marks (such as scars, moles, and wrinkles). Morphological analysis is carried out methodically and contains a pre-determined list of the features to be compared for each examination. This makes it easier to structure comparisons, document them, and replicate the identification process. Morphological analysis is a subfield of forensic morphology. Morphological analysis is a subfield of forensic morphology. There are several facial feature lists available however, the FISWG and ENFSI do not presently recommend any particular list [10] [11] [12].

Morphological comparison is typically sensitive to a loss of image quality (such as blurring or a reduction in spatial resolution), a reduction in the visibility of gross details (such as the specific shape of the eyes, mouth, and nose), and a reduction in, or elimination of, the visibility of fine details. Morphological comparison can also be sensitive to the presence of noise in the image (e.g. freckles, creases on the face). Photo-anthropometry is a method used to quantify the characteristics and proportions of anthropological markers and other facial features. It is predicated on evaluating a range of dimensions (such as spatial distances, angles), anthropological markers, and other facial features [13]. After collecting these metrics, a comparison is made between two different face photographs to establish the degree of resemblance or dissimilarity between the two. Absolute measurements on their own are an extremely unreliable method of comparison. On the other hand, normalized proportionality indices, which are more appropriate because they are estimated as a ratio between two absolute measurements, do have some advantages. However, they also have some drawbacks. The application of indexes does not solve difficulties caused by extrinsic variables such as the subject's distance from the camera, the focal length of the lens, the camera angle, or the head's position. Therefore, indices and angles are required to be utilized in situations in which the precise placements of the cameras and the subject-to-camera lengths are known. In addition, photo-anthropometry is highly sensitive to a loss in image quality (such as blurring, a reduction in spatial resolution, lens distortion, or viewpoint distortion), which decreases the capacity to decide the precise location of landmark points and, as a result, decreases the exactness of all measurements [14].

The Foundation of the Techniques

Facial Feature analysis:

The primary way in which an individual presents themselves to society is through their facial characteristics. These characteristics distinguish an individual from others since they possess a collection of distinctive qualities that enable them to be individualized.

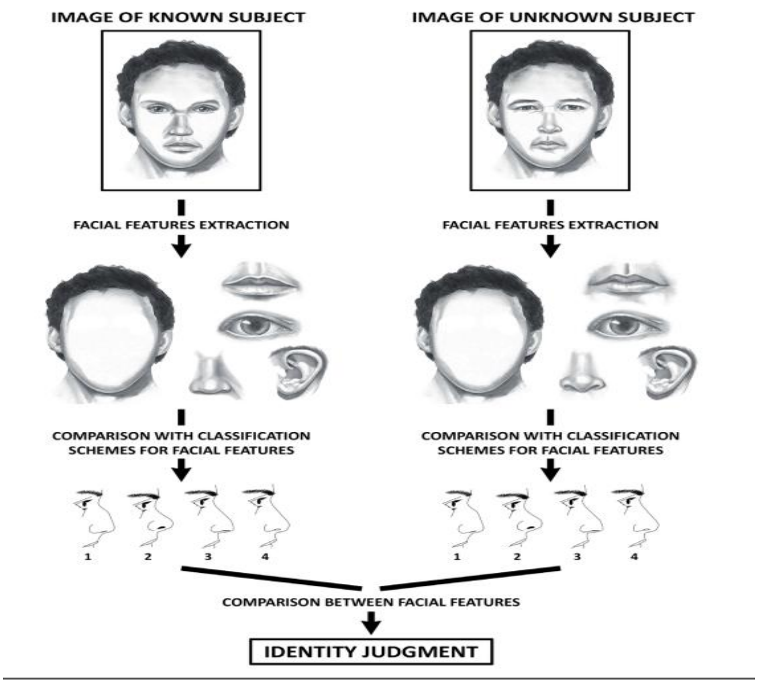

Fig. 1 Flow diagram showing how global and regional facial traits are characterized for identification conventionally.

1) Facial Structure: The structure of the face is the first factor to take into account. The proximal portion of the cranium categorizes the arrangement of the face just above the superciliary arch off to the jaw that has a sequence of forms in the frontal norm. According to [9], there are various facial shapes (Fig. 2). They are as follows:

a) Elliptical; b) Oval; c) Inverted Oval; d) Rounded; e) Rectangular, f) Quadrangular; g) Rhomboidal; h) Trapezoidal; i) Inverted Trapezoidal; and j) Pentagonal.

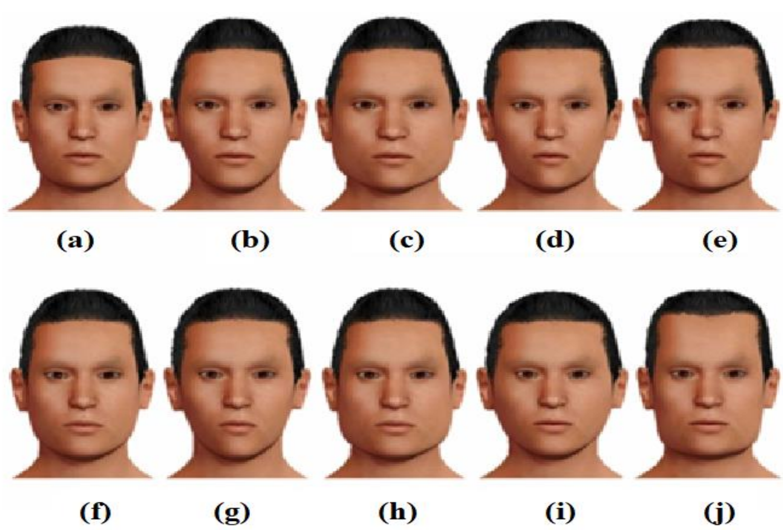

Fig. 2. Various Facial Shapes
(*Source: https://www.sciencedirect.com/science/article/pii/S2665910722000093#bib10*)

This is reflected in terms of each of the dissimilarities in the geomorphologic areas of the skull [15].

2) Nose: The nose is among the unique attributes in determining an individual's identity because of the wide range of components that make each person's nose unique. The study of the nose's anatomy is used to categorize it based

on its features, such as the nose root, body tip, nostril, ala, and nose base [16]. The nose's morphological traits rely on various indexes based on its shape presented in table 1.

Table 1. Nasal Morphology Index of Human

Class	Nose form	Index
Hyper-leptorrhine	Very slender	40.0-54.9
Leptorrhine	Extended + slender	55.0-69.9
Mesorrhine	Moderate form	70.0-84.9
Platyrrhine	Wide + small	85.0-99.9
Hyper-platyrrhine	Wide	Greater than 100

3) Eye: The color of the pupil, the folds, as well as the lid, and the shape of the eyebrows, are all taken into account when it comes to the eyes.

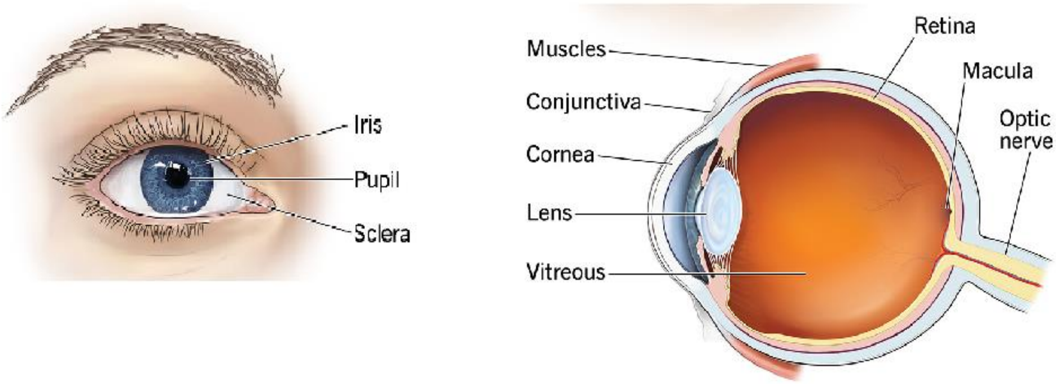

Fig. 3. Anatomy of the eye

4) Lip: In the case of lips, the vermilion border, the width of the lips, and the form of the commissures are all factors that are analyzed and compared to one another. The fundamental characteristics of the lip's morphology might vary substantially from person to person.

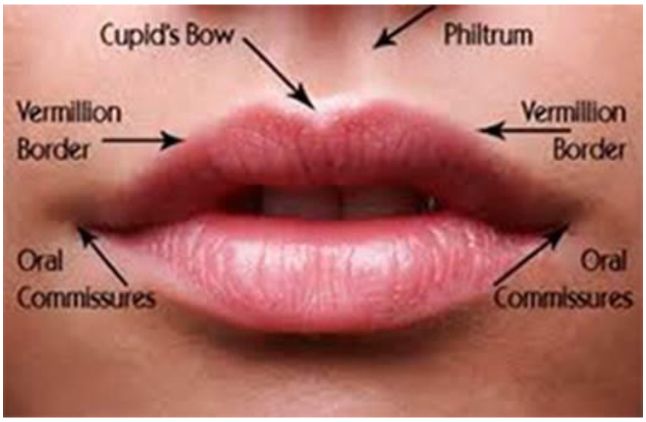

Fig. 4. Lip morphology
(*Source:3D Face Morphology Classification for Medical Applications* [17])

5) Ear: The various features of ear-anatomy are essential for the facial feature analysis from the images. For instance, the helix and antihelix are extensively researched and investigated in the ear [16]. Additionally, the lobe is also investigated using this method.

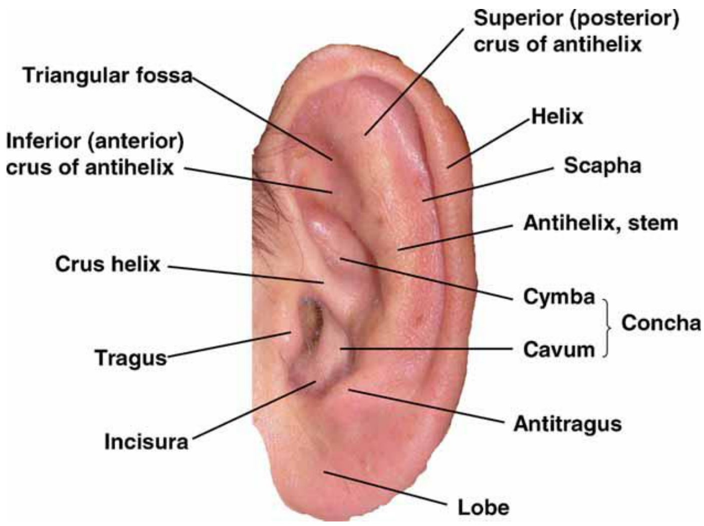

Fig. 5. Morphology of human ear
(Source: *https://elementsofmorphology.nih.gov/anatomy-ear.shtml*)

6) Cheekbones and Chin: When describing the cheekbones, the width or breadth, and elevation, including protrusion or retraction, are all important aspects to consider. In addition, the projection, thickness, as well as distribution of the mentonian tubercles and the protuberance are investigated in the chin [9].

Identification by Medical Anthropology:

When it comes to legal conflicts, FA utilizes physical anthropology [18], which is the study of the human body, and places a particular emphasis on the skeleton. FA approaches, in comparison to other methods of identification (such as fingerprints and DNA testing) [19], provide an alternative and an equivalent that can be utilized in a significantly greater range of situations. According to the Scientific Working Group for Forensic Anthropology findings, there are two stages in the documentation process in which forensic scientists can be of assistance [20]. The first thing that needs to be done is to collect positive identifications using a variety of methods. By narrowing down the pool of candidates for a match at the second level, an individual can be singled out for identification. It includes various procedures described in [21]. The approaches, on the other hand, are far more difficult to implement. Biometric profiling has been explored for over three centuries, and now it plays an important part in reducing the spectrum of different matches throughout the analysis procedure [22]. In this profiling, skeletal remains are examined in order to identify an individual by looking for distinguishing characteristics. The estimation of gender, age, height, and ancestry is done in this specific order [23]. The characteristics of biological profiling is described below.

1) Adults' sex assessment is a difficult procedure. The morphological characteristics of the cranium and the pelvis should be used. When this is not possible, the vestigial skeletal discriminating formulas should be employed instead [24] [25]. Before moving further, it is essential to have an accurate understanding of gender to achieve the greatest possible outcomes.
2) Another task is to determine the children's sexual orientation. It is important for researchers to discern the sexual orientation of children when they are studying adolescents or sub-adults. However, alternative approaches, such as the analysis of the morphological features of the ilium, particularly the sciatic notch, have shown a significant potential [26].
3) For the determination of the age of deceased adults performed according to the method given in Btoks *et al.* (1990) is advised for the study of the pubic symphysis' degenerative processes [27]. According to Baccino *et al.* (1997), the two-step process given by Lamendin *et al.* should be used to combine this method with the investigation of canine root transparency [28] [29]. When this isn't an option, the most reliable approaches are those proposed by Lovejoy *et al.* for analyzing the coxal atrial veneer; Iscan *et al.* for analysing the sternal end of the fourth rib; and Meindl *et al.* [30] for analysing the processes of obliteration of the cranial sutures, which is the least foolproof tool but the only one available in many cases [31] [32] [33].

4) For persons who have not yet entered adulthood, such as children, the approaches that Scheuer *et al.* proposed in 2004 are advised as the best way to determine their age after death [34].
5) Long bones are used in height determination because of their length. It is advised to utilise the formulas presented in Nunes *et al.* [35] for the femur and humerus, and the formulas provided in the book called *'Estimation of height through the tibia in contemporary Spanish population'* [36] for the tibia, when the remnants are contemporaneous and originated from the Mediterranean. The mathematical models suggested in Trotter *et al.* [37] and the FORDISC computer programme [38] are the ones that will most likely be used to study the remains in the event that they come from a North American population.

All of these traits are required for facial image analysis.

Importance of Orthodontics in Forensic Facial Image Analysis:

Orthodontics is a subspecialty of dentistry that focuses on diagnosing, treating, and preventing developmental and positional irregularities of the teeth and jaws, particularly as these irregularities relate to a person's oral health and overall physical, mental, and emotional well-being. The study of the craniofacial skeleton, the diagnosis and treatment of craniofacial anomalies, molar region interactions, tooth mal-positioning, and longitudinal features of changes in hard and soft tissue with ageing are all topics covered by this specialty. FFA is the application of the science of reconstructing a face to generate a resemblance to the face of the departed, both for scientific and forensic applications [39-41]. It is a highly-trained method based on the basic scientific concepts of skeletal anatomy, odontology, forensics, and the arts [42]. Orthodontists trained in the face's hard and soft tissue structure can contribute their knowledge and expertise to rebuilding a more natural-looking face [43]. Orthodontists utilize various photometric points to reconstruct the face. In the classic FFA method, there are three components, namely:

1. Anatomical mapping,
2. Identification of facial structure
3. Facial reconstruction

Table 2. Various Stages in Forensic Facial Approximation

	Stages	Sub-category
1.	Evolutionary trends	
2.	Reference planes on the skull	
3.	Dental profiling	a) Articulation of jaws and teeth
		b) Measurements and morphologic characteristics of teeth
4.	Skull and soft tissue profiling	a) Facial soft tissue thickness
		b) Growth and age changes
		c) Growth pattern/facial types
		d) Nose prediction
		e) Cephalic and facial indices
		f) Facial symmetry and proportion
5.	Ante-mortem records for comparison	
6.	Exposure to software and 3D facial imaging	

It establishes a multidisciplinary method for FFA, encompassing divisions of anatomy, biological or physical anthropology, as well as forensic science, where the individual cranial and facial skeleton, as well as soft tissue, are analyzed from the standpoint of either evolution or development. During facial restoration, dental skull profiling can be very valuable and raise the chances of restorative recognition. Many distinct developmental possibilities can be helpful. The development of the masticatory complex, cramming, projection of top incisors, surface roughness status, etc are some of the factors that can play a role in this.

Facial Growth on Skull using AI

The study literature provides a variety of various recommendations for carrying out the SFO task in the appropriate manner. Reproducing the original setting of the AM image, in which the real person stood in a specific stance somewhere inside the camera's field of vision, is the most natural method to solve the problem of SFO. This is because the original setting was captured when the AM image was taken. This is also the one that requires the maximum amount of time. In terms of computer-aided automated processes, the major goal of the SFO process is to complete the task of reproducing on a skull the location and the other acquisition characteristics of a specific face shot. This is done by transferring the information from the original face shot onto the skull. This may be accomplished by making a duplicate of the photos and pasting it onto the skull. This is akin to the age-old task of reconstructing the posture of a three-dimensional item from an image using only a few reference points as a guide. In this case, you only have a few reference points to work with.

In the year 2021, Niloofar *et al.* presented the first computer-aided approach for the SFO challenge [44]. In order to match the landmarks of the 2D face photo with those of the 3D skull model, affine and perspective transformations (rotation, scaling, and translation) had to be computed with the help of real-coded genetic algorithms. The landmarks of the 3D skull model were chosen for this purpose. Another automated technique was explained in this report, in which the authors assessed the use of two separate neural networks to assess the uniformity between two approximately frontal 2D pictures objectively. This method was able to determine the degree of symmetry between the two images (skull and facial image). Over the course of the last decade, a number of academics have endeavored, via the use of evolutionary algorithms and fuzzy sets, to automate the SFO process. In order for these techniques to be effective, a three-dimensional model of the skull is layered on top of a picture of the subject's face. In order to do this, they shorten the distance between neighboring landmark pairs and, at the same time, take into consideration the imprecision that is brought on by the position of the face landmarks. While executing the reduction method, it is vital to search for a certain projection of the skull model that will result in the most exact matching that is practicable between the various landmarks. This will allow for the most successful reduction.

A revolutionary new automated SFO approach called POSEST-SFO was only recently introduced by Valsecchi *et al.* (2018) [45]. The POSEST-SFO technique, in contrast to other approaches, resolves a set of polynomial equations that link the spaces amid points both before and after the projection. These equations are related by the fact that they relate the distances. In order to determine the new distances that exist between the sites, these equations are utilized. This latter strategy was assessed using a synthetic data set containing 9 computed tomography scans (CBCTs) obtained from 9 unique persons and 60 generated photos, for a grand total of 540 SFOs. The simulated photographs were created using the same settings as the real pictures. Due to the fact that it only 78 milliseconds for it to automatically carry out a single SFO, this method is highly efficient. When the most plausible situation was taken into consideration, the average back-projection error for frontal images was found to be 2.0 millimeters, while the error for lateral photos was found to be 3.2 millimeters. This scenario considered the thickness of the soft tissue by using the mean distance, and it allowed for a margin of error in facial landmarks equal to 5 pixels. In contrast to other research, this technique does not address the various causes of indecision. These sources include the enunciation of the jaw, the measurement of the soft flesh thickness, and the intra- and inter-fault in the position of landmarks.

Methods

For a very long time, people from a variety of academic backgrounds, including anthropologists, artists, and philosophers, have been employing methods from both the aesthetic and anthropological fields in their research on the human face. In the process of identifying offenders, forensic anthropologists frequently seek the professional opinions of anthropologists who specialise in certain subfields of the discipline, such as facial comparison. The process of matching photos of a criminal with images of a suspect is known as forensic face analysis [46].

Many studies have been developed over the years for the domain of forensic analysis using facial recognition for many applications including the application of criminal identification. One method for this is the determination of the biological profile (BP), which has been the subject of research for over three hundred years, and is currently an extremely important factor in the identification process, as it helps to limit down the pool of candidates for a possible match. The practice of BP entails the examination of human bones with the intention of locating distinctive features that lend assistance to the determination of the individual's identity. The estimation of ancestry, age, height, and gender all take place in the specific sequence outlined above since it is a step-by-step process. Numerous studies that used AI for this estimation are present. In order to train and verify the model, Larson *et al.* (2018) [47] employed a ConvNet across a collection of 14,036 medical hand radiographs and its related studies, acquired from two children's hospitals. The RMS of a second test set made up of 1377 assessments from the openly accessible GP Digital Hand Atlas [48] was assessed with an spontaneous system already in existence called BoneXpert from radiographs of palms and fingers with the help of a predictive model (active appearance model), and then forecasts the age as from shape, and intensity. It is crucial to note that this program is not utilized in forensic contexts for age estimation; rather, it is used in clinical settings to measure bone maturity and discover abnormalities/diseases. Three human reviewers, the clinical report, and the model's estimations all fell within the 95% ranges of agreement.

Dallora *et al.* (2019) developed a deep learning system that can recognize and separate the hand and wrist automatically [49]. They use a fine-tuned ConvNet to achieve an automatic bone age assessment on a collection of 4278 women and 4047 men radiographs (with temporal ages ranging from 5 to 18 years old). For said female and male groups on the held-out test picture, their model had accuracy rates of 57.32 percent and 61.40 percent, respectively. Using a collection of feature points upon this hand, Lee *et al.* (2020) demonstrated how to apply DL for age estimate from a subject's hand X-ray pictures [50]. For the purpose of cropping a specific region that is instructive in terms of aging-induced morphological changes, these points must be specified. Mutasa *et al.* (2018) [51] achieved a test set MAE of 0.637 and 0.536, respectively, using their suggested customized neural network architecture taught on 10,289 pictures of varied skeletal ages. Their findings are consistent with the claim that networks created specifically for a task offer superior performance than those created using pre-trained image data.
An in-depth assessment may be found in Rani *et al.* (2020), which divides automated attempts to recreating the TW2 method into two categories based on whether they employ image processing or expertise techniques [52]. The bulk of technologies based on image processing were developed in the 2000s. These techniques train classifiers using hand radiographs of real people as their knowledge source. Chen *et al.* (2020) proposes an algorithm for skeletal maturity evaluation based on computing with words [53]. The suggestion is based on the output of a neural network and a fuzzy filter. Mansourvar *et al.* uses a fuzzy inference technique to determine age [54]. Recently, many DL techniques were developed and evaluated by Pan *et al.* (2020) [55]. The TW2 approach and a dataset with roughly 1400 X-ray pictures are specifically used to estimate skeletal bone age automatically utilizing a number of pre-trained ConvNets that already exist. According to the findings, there is typically a 0.8-year difference between manual and automated evaluations.

Another way of identifying a person is through AI-based traumatism and pathology analysis approaches. Many studies have also been conducted in this domain. Such as 256,000 wrist, palm, and ankle radiographs were taken from Danderyd's Hospital and classified into 4 categories by Nagy *et al.* (2022) [56] for fracture, laterality, body component, and exam view. The accuracy of five publically accessible deep networks that were optimized for this purpose was then assessed. When detecting laterality, body part, and exam perspective, all networks had an accuracy of at least 90%. For the top-performing network, the accuracy level for fractures was predicted to be 83 percent. Plain anteroposterior shoulders radiographs were used by Chung *et al.* (2018) [57] to assess the effectiveness of AI approaches for identifying and categorizing proximal humerus fractures. 1891 photographs (1 image per individual) of normal shoulders (n = 515) and 4 forms of proximal humerus fractures (greater tuberosity, 346; surgical neck, 514; 3-part, 269; 4 part, 247) were included in the assessed dataset. These fracture types were identified by three experts. According to their findings, normal shoulders could be distinguished from proximal humerus fractures with 96 percent accuracy, and the kind of fracture could be identified with 65–86% accuracy. Through an increase in the limited amount of positive data in the training set, Gupta *et al.* (2019) solve the issue of identifying bone fractures from X-ray pictures [58]. They provide a generative data augmentation method that generates bone lesions on pathology-free pictures using a cycle-consistent generative adversarial network. Peripheral bone and anatomical characteristics of the human body are included in the category of forensic anthropological identifiers. Alterations to the skin and the physical features of the face, dentition, and other related parts are included in the category of external features. The evaluation of morphological traits such as facial attributes and skin variations, which may be analyzed using the approach of facial appearance assessment, is within the purview of forensic anthropologists' areas of expertise. In numerous nations of Europe, forensic anthropologists play the role of expert witnesses in comparing face images, and they are frequently engaged as experts in this field [21].

The identification of gender from human remains is a difficult problem in several disciplines, including archaeology, physical anthropology, and forensics, due to the lack of a definitive classification technique. The application of artificial intelligence in this area is extremely favorable, as the guided decision is frequently tedious and time-taking. The objectivity of deep learning may also reduce humankind's prejudice, resulting in trustworthy software solutions. AI-based age estimate has shown to be a formidable rival to traditional forensic medical techniques. This research aims to develop an automated technique for estimating age using 3D cranial CT images. There is a presumption that specific areas of the skull have a decisive effect on the ultimate prognosis. Age estimation from a thick tissue layer uses a CT scan of the entire skull as data to a 3D CNN, that serves as a regression system. It predicts the consistent age data for all CT scans [59].

The cephalometric analysis aims to establish CT scans' landmarks, which play a crucial role in skull alignment. These measures can also be utilized as operation planning criteria or for comparing pre- and post-operative conditions. The concept underlying method is utilizing 3D convolutional neural networks for completely automated cephalometric analysis. The objective of networks is to generate probabilistic estimates for every cephalometric landmark and then project these estimates onto a real skull CT image [60]. Using the SAFF-2D software, a group of specialists identifies 28 cephalometric landmarks in each of 1000 pre-training photos [13]. Following the proposed approach, all 18,000 faces and all facial features were documented and examined. Following is a comprehensive list of recognized cephalometric benchmarks rendering to Caple and Stephan's standard terminology: The bilateral markers Endocanthion (en'), Exocanthion (ex'), Iridion laterale (il), Iridion mediale (im), the pupil (pu'), Zygion (zy'), Alare (al'), Gonion (go'), Cheilion (ch'), and Crista philter (cph'). Glabella (g'), Nasion (n'), Subnasale, (sn'), Labiale superius (ls'), Stomion (sto'), Labiale inferius (li'), Gnathion (gn'), and Midnasal (m') are located on the midline of the face [61]. Photo-anthropometric indices (PAIs) are face parameters that interpret anthropometric data, namely age and sex, using only physical growth data [62]. 208 PAIs per image were fed to an automated classifier in order to assess anthropological information. k-fold cross-validation was utilised in the testing procedure to evaluate the predicted performance of the classifier model over the provided data set. To assess the PAI approach for anthropological estimate, three groups of experiments were established. Group A deals with the estimation of sex, Group B with the approximation of age, and Group C with the estimation of the age group [13].

Discussion

The drawback of using anthropological identifiers is the scarcity of researches and case reports that provide applicable procedures for the quantitative analysis of the results. In the field of forensic odontology, this apparent flaw is likewise an issue that is frequently disregarded. Forensics experts are advised to enter the future age of AI as a beneficial technique for investigating and maybe even routine forensic evaluations. The application of 3D CNN to specific forensic subjects (Biological years old determination, gender prediction, 3D cephalometric assessment, and Head prediction from skull) can be utilized as a starting point. Forensic 3D reconstructions will be innovative, fascinating, and practically applicable techniques using artificial intelligence. Sophisticated AI implementation still requires inter-disciplinary collaboration, but it may be utilized to solve unsolved puzzles. The use of photo-anthropometric assessment to examine the parametric development of the human face by categorizing persons adds to the investigation of facial changes through time. The previous methodology illustrates the benefits emphasized in the sample stratification into four distinct age periods and the gathering and measurement of significantly more information gleaned from the human face's morphology. The F1 score of each group was evaluated.

Conclusion

In this article, we have provided a review of some of the most important works that apply AI systems to various biomedical image modalities (primarily X-ray images, CTs, and MRIs, but also 3D surface scans of PM materials, such as bone remnants), with the intention of subsidizing to the forensic human identification of both living and deceased persons. SFI is one of the primary tools that we have available to us when other investigative methods, such as DNA study or fingerprint assessment, are unable to be used for one of several reasons, including the absence of a second sample to use for comparison or the extreme degradation of the materials, which prevents the preservation of soft tissues. The use of AI methods has shown to be highly successful in a wide variety of difficult jobs, including those about healthcare and medical imaging. When seen from this angle, the continued use of AI in the day-to-day work of forensic anthropologists is a very unexpected development that comes as quite a shock. Even if certain crucial technologies start to emerge in the future, forensic specialists do not yet have access to AI-based tools that can automate SFI activities at this time.

Certain way outs discussed in this study use CV, SC, and ML approaches for spontaneous recognition methods like CFS or CR. This is accomplished over the objective with precise treating, scrutiny, and evaluation of AM and PM data. In addition, some of the proposed methods would make it possible for rapid repeated comparisons. It would provide effective filtering capabilities that would cut down on the number of possibilities in a database in a matter of minutes rather than hours or days. Conversely, choices might be backed on impartial and reproducible information, which may have a greater influence in a court of law. Other methods can contribute to the automatic performance of the graphic assessment of structural features with a great level of accuracy, and they can eliminate human partiality in altogether.

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