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Applications of artificial intelligence in age estimation: a review

Abdulkadir Sancı, Burak Kaya

Forensic Medicine Specialist, Artvin Forensic Medicine Branch Office, Artvin, Turkiye

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Corresponding Author: Abdulkadir Sancı, akadirsanci@gmail.com

ABSTRACT

Age estimation is a legally significant issue, particularly in underdeveloped and developing countries, due to factors such as inadequate civil registration systems and irregular migration. While various techniques are employed for age estimation using traditional methods, it is known that factors including age, gender, chronic illness, race, and geographical region can result in discrepancies between skeletal age and chronological age. This complicates the process of achieving accurate age estimation. This review aims to discuss recent research on artificial intelligence applications in light of current literature. Artificial intelligence and machine learning (ML) have enabled machines to acquire human-like capabilities in thinking, learning, problem solving, and decision making, leading to significant progress in achieving faster and accurate results. In the field of forensic medicine, methods such as linear discriminant analysis, K-Nearest Neighbors, support vector machines, random forests, and artificial neural networks have been employed to classify data and conduct studies on age estimation. In the research, age estimation was made by focusing especially on the carpal bones, ossification centers, middle phalanx of the hand, third metacarpal, radius and ulna regions. Additionally, facial angles and width obtained through tomographic examinations, as well as measurements of the calcaneus and cuboid bones, panoramic dental radiographs, volumetric analysis of teeth and pulp using cone beam computed tomography, and analysis of bloodstains on microRNAs, have been analyzed for their distribution across different age. The results demonstrate that artificial intelligence applications can be utilized in age estimation with a high accuracy rate (85-95%). Age estimation using artificial intelligence enhances data-driven decision-making processes, improves the quality of services, and contributes to societal benefit. Therefore, we believe that incorporating artificial intelligence applications alongside traditional methods in age estimation will yield more meaningful outcomes.

Keywords: Age estimation, artificial intelligence, radiology, forensic medicine

INTRODUCTION

The term “identity” refers to all characteristics that are effective in recognizing, identifying, and distinguishing an individual from others. The process of identifying these characteristics in both living individuals and postmortem examinations is referred to as “identity verification.” Identity verification is a necessary practice for both living individuals and deceased persons for various reasons. In contemporary times, the identification of individuals has transcended being merely a personal or societal issue, gaining international significance. One of the critical elements of identification is the determination of a person’s age. Physical characteristics such as age, gender, height, weight, hair type, skin tone, eye color, fingerprints, bone structure, and dental structure are among the key aspects of identification.[1]

THE IMPORTANCE OF AGE ESTIMATION

It is a fundamental human right for individuals to know their true age. Age estimation serves as an important document that completes and validates an individual’s identity characteristics. For instance, it has been observed that the Romans used the eruption of the first permanent molars in the mouth to determine whether a person was of military age, indicating the use of teeth in age estimation.[2]

For individuals whose birth dates have not been reliably recorded, forensic age estimation is required. Today, forensic age estimation is a significant area of evaluation, particularly in civil and criminal law. The reasons for requesting forensic age estimation can vary between countries and regions. In Turkey, the primary reason for this need is the late registration of children in the population registry, especially in rural areas. For individuals whose population registry information is questioned, forensic age estimation is also requested in legal processes concerning criminal law, as well as for living individuals in situations such as school enrollment, job applications, marriage, and military service.[3] In recent years, migration has become a significant global issue. The intense migration and the lack of official documents among migrants have necessitated age estimation for identity verification, making this a global concern. Age estimation has gained importance in migrants in terms of verifying their identity, accessing social services, and in potential legal processes and judicial proceedings if they commit or are subjected to crimes.

In forensic medicine, age estimation, whether for living individuals in the antemortem period or for deceased individuals in postmortem examinations, holds great importance in both criminal and civil law.[4] As in the past, today, the determination of an individual's true age is crucial in determining their criminal and legal responsibility, their capacity to comprehend the legal meaning and consequences of their actions, their psychological protection in cases of sexual assault, the determination of the age of suspects in criminal acts, as well as in situations such as school enrollment, entering public service, retirement, and obtaining a driver's license.[5] Additionally, forensic authorities request age estimation for unidentified individuals or infant corpses.

In criminal law, age groups in Turkey are categorized into three groups: 0-12, 12-15, and 15-18 years. Similar age groupings are made in other countries as well. In Germany, the age groups are 0-14, 14-18, and 18-21 years; in England, 0-7, 7-14, and 14-17 years; in France, 0-13, 13-16, and 16-18 years; and in Russia, 0-14, 14-18, and 18-20 years. Switzerland categorizes age groups into four groups: 0-7, 7-15, 15-18, and 18-25 years. In Turkey, discrepancies between the actual age and the age recorded in the population registry are more frequently encountered at critical ages from a legal perspective, such as 12, 15, 18, and 21 years. Many laws in Turkey define the age factor. Additionally, the Population Law specifies how population records should be corrected and who is authorized to request these corrections. Article 7 of the Civil Code, under the heading of proof with official documents, states that official registers and records are deemed to validate the accuracy of the information they document. Unless another regulation is specified in the laws, no specific formal requirement is needed to prove the inaccuracy of these documents. It is emphasized that if an individual was born in a hospital or has an official birth certificate, the court should give priority to these documents. In such cases, a medical report is not required for age estimation.[6]

In our country, discrepancies between the declared age and the actual age often arise due to late population registrations or the use of the identity information of a deceased child for a newborn. Furthermore, issues such as concealing age information or using false identities can lead to various problems in situations requiring age-based restrictions, such as migration, inheritance, legal cases, sports, and retirement.[7]

METHODS USED IN AGE ESTIMATION

Age estimation methods are categorized into three main categories: radiological, morphological, and histological. Among these, radiological and morphological methods are the most frequently used. The criteria evaluated in these methods cover a broad spectrum. Key criteria include height, weight, signs of adolescence, hair, skin changes, eye changes, psychological state, teeth, and bone development. Physiological and pathological factors affecting an individual's development, physical findings such as height, weight, dental development, signs of puberty, psychological and mental development, and radiological assessments of ossification between the epiphysis and metaphysis of bones and the timing of physiological calcification of bones are examined.[3]

In radiological examinations, primary atlases prepared according to the standards of Western societies are used for comparison. These include the Greulich and Pyle (G-P) atlas, Tanner-Whitehouse (T-W) scoring, and the V. Gilsanz-O. Ratib atlas. Radiological analyses assess whether the epiphyseal lines of bones have closed, changes at the vertebral and sternal ends of the ribs, the calcification states of the sternum and sacrum, the formation of osteophytes due to senility, and changes in the internal structure of bone tissue (e.g., osteoporosis, thinning of the trabeculae in the medulla). These methods are among the most commonly used and reliable techniques for age estimation. Radiological methods such as the formation and development of growth plates in bones, the evaluation of epiphyseal and diaphyseal lines, and the determination of ossification points play a significant role in clinical applications for age estimation and provide results closest to reality.[9]

For radiological examinations, hand-wrist radiographs are considered for bone development stages under the age of 12, while hand finger and metacarpal bones, lower epiphysis radiographs of the radius and ulna, anterior and lateral elbow radiographs, shoulder radiographs showing the humerus neck, and unilateral pelvis radiographs including the iliac upper and ischial lower edges are used for age estimation between 12-22 years. Sacrum and lateral coccyx radiographs are examined for ages 23-40, lateral sternum radiographs around age 40, and anterior chest radiographs between 45-50 years.[1] Some national studies have used clavicle medial epiphysis for computed tomography staging to determine age between 19-21 years,[10] while other studies have used tomography to examine the degree of sacral vertebral fusion,[11] bimastoid width measurements,[12] and face-ear distance measurements[13] for age estimation.

In forensic dentistry, archaeology, and forensic medicine, various methods are being researched to determine the age of skeletal remains or unidentified bodies with minimal margin of error. Advances in forensic odontology have contributed to the increase in dental examinations and the acquisition of more accurate results. Teeth are often used for age estimation in identification. Due to their hard structure and low metabolic rate, it is suggested that the data obtained from dental development provides more accurate results than other structures in the organism.[14]

The evaluation of dental tissue has long been considered a reliable tool for age estimation, and techniques applied to these tissues have been widely used by forensic dentists, forensic pathologists, and anthropologists. The scientific rationale for dental tissue evaluation in age estimation is based on three criteria: 1. Formation and growth changes of teeth, 2. Post-formation changes, 3. Biochemical changes.

The formation and growth of teeth encompass the morphological development of the crown, root, and apex points of the tooth, including the emergence, eruption, and progression stages. An important advantage of age estimation using dental formation and growth techniques in forensic dentistry is that they are non-invasive and can be easily evaluated through inspection and radiographic examination. Once growth in teeth and bones ceases, forensic dentists employ techniques involving the biochemical changes or post-formation changes of the teeth for age estimation: aspartic acid racemization and Carbon-14 age testing. Both are expensive and time-consuming laboratory techniques that examine tooth structure.[15]

One of the age estimation methods is the histological method. Recent studies in this field have focused on histomorphological and histochemical techniques. These methods estimate age by examining characteristics such as bone structure, muscle fiber types, and myosin heavy chains. Additionally, examining cell proliferation using the AgNOR staining method on abdominal skin samples from age groups has emerged as an alternative approach to age estimation. The clinical applicability of these methods provides significant clarity in cases where definitive age estimation is not possible. However, because new methods have not yet been standardized to provide consistent and reliable results, existing methods still play an important role.[9]

Another important aspect of age estimation is identifying endocrine diseases that affect growth and development and evaluating the extent of their impact. Various metabolic, hormonal, and genetic diseases that can lead to early or delayed bone development include obesity, diabetes, hypothyroidism, growth hormone deficiency, celiac disease, ulcerative colitis, nephrotic syndrome, goiter, hypercalcemia, phenylketonuria, Down syndrome, Turner syndrome, and Angelman syndrome. Additionally, factors such as gender, race, socioeconomic status, and trauma can also influence this condition (**Table**).[16] There is very limited national and international literature on the impact of growth and development-affecting diseases on age estimation, particularly in children with diabetes, obese children, pregnant or previously pregnant children, genetic malformations, and other growth-impairing conditions. In studies on age assessment in diabetic children, Dost and colleagues reported in 2010 that in their study of bone development in 1788 German and Austrian children diagnosed with type 1 diabetes, the bone ages of diabetic children and adolescents were significantly delayed, with the difference ranging from 0.27 to 1.1 years. Those over 16 years old showed more pronounced bone age retardation compared to other cases. It was also reported that the delay in bone age in males was more significant than in females. Bone age was found to be significantly delayed in individuals with high HbA1c levels and poor glycemic control from the onset of diabetes to the determination of bone age.[17] It has been reported that all these traditional methods commonly used in forensic age estimation may result in inaccuracies due to factors such as the lack of data in new research and statistical analyses, individual differences, and environmental factors. This situation complicates the achievement of accurate age estimation. However, with the advancement of technology, the use of artificial intelligence (AI) applications has increased; studies have reported that higher accuracy results can be achieved in forensic age estimation through artificial intelligence.

Table 1. Causes of discrepancy between bone age and chronological age 2

Bone age <chronological age	Bone age >chronological age
Hypothyroidism (congenital & acquired)	Precocious puberty
Growth hormone deficiency	Premature adrenarche
Panhypopituitarism	Congenital adrenal hyperplasia
Hypogonadism	Hyperthyroidism
Constitutional growth delay	Constitutional tall stature
Rickets	Obesity
Corticosteroid excess syndromes (Turner, Down, Klinefelter, Silver-Russell)	Overgrowth syndromes (Sotos, Beckwith-Wiedemann syndrome)
Malnutrition (primary or secondary to chronic disease)	

ARTIFICIAL INTELLIGENCE AND COMMONLY USED METHODS IN DATA ANALYSIS

AI can achieve faster and more accurate results than humans in data analysis, identifying connections between data, and making predictions. AI algorithms, often working with large datasets, can effectively analyze biological features for age estimation. For example, it is possible to estimate age through the analysis of radiological images of bones and teeth.[18]

The primary function of AI is to classify uploaded data and develop algorithms that evaluate the relationships between these data. Among these classification techniques is Linear Discriminant Analysis, which reduces a two-variable dataset to a single variable and draws a linear boundary between classes (**Figure 1**). Other classifiers, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest, and Bagging, have the ability to create non-linear boundaries between class samples.

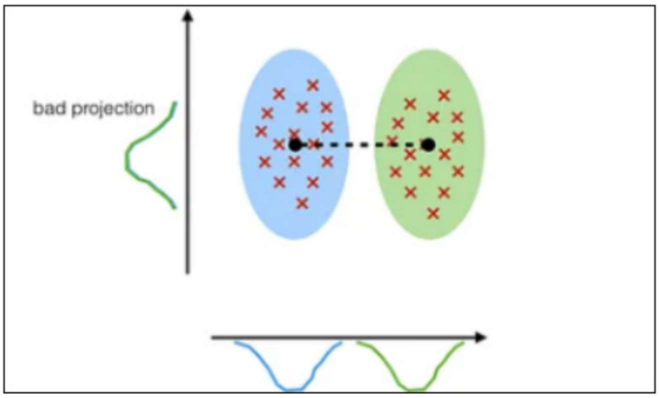

Figure 1. Linear Discriminant Analysis (LDA)

KNN is one of the most widely used ML algorithms. When a test sample is added to the KNN classifier, the number of nearest neighbors, denoted ask, is first determined (**Figure 2**). This algorithm makes predictions by examining its neighbors. The assumption in the KNN algorithm is that similar objects are close to each other.[19]

Another effective statistical classifier frequently used in small and medium-scale applications is Support Vector Machines (SVM). SVM aims to enhance the separation of examples in a new high-dimensional space by transforming the inputs into this space (**Figure 3**). It groups the data by drawing linear or non-linear curves.[20]

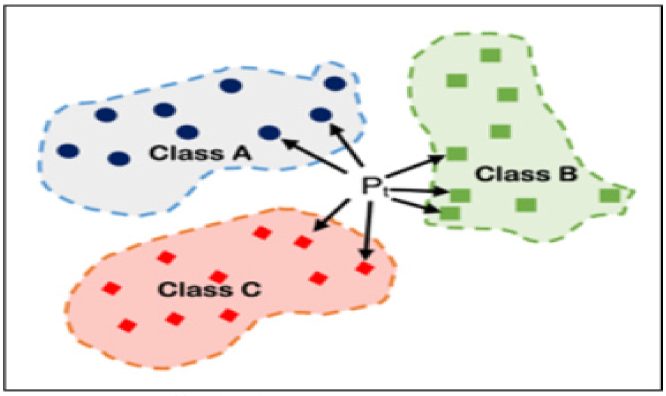

Figure 2. K-Nearest Neighbors (KNN)

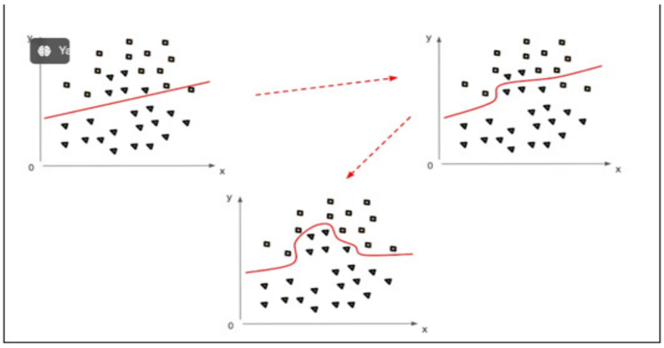

Figure 3. Support Vector Machines (SVM)

Decision trees is a method that has many real-life similarities and impacts a wide range of ML areas, encompassing both classification and regression. A decision tree can visually and comprehensibly present decisions and decision-making processes within the framework of decision analysis (**Figure 4**). As the name suggests, it forms a decision model using a tree-like structure.[21]

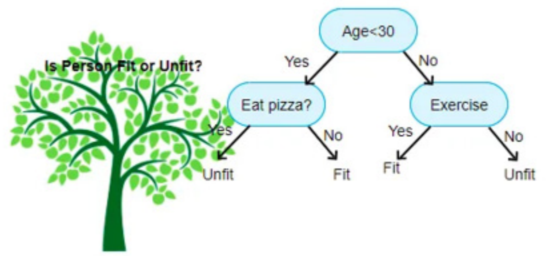

Figure 4. Decision tree

Random Forest, as the name suggests, primarily involves the algorithm creating a random forest (**Figure 5**). There is a direct relationship between the number of trees used in the algorithm and the results obtained. Increasing the number of trees yields more accurate results.[22]

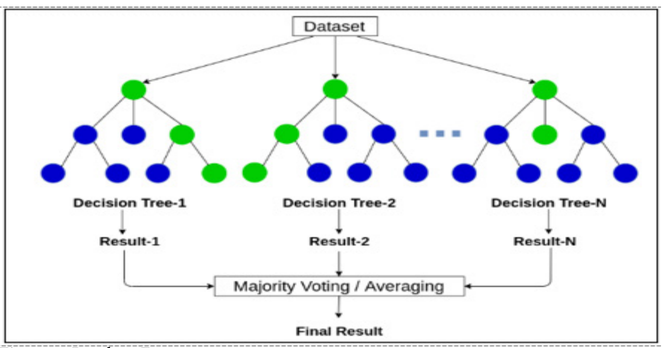

Figure 5. Random Forest

Artificial Neural Networks (ANNs) are a computational technique developed by mimicking the information processing methods of the human brain. ANNs simulate the functioning of biological neurons and the synaptic connections between these cells. Neurons combine in various forms to create networks (**Figure 6**). These networks have the ability to learn, form memories, and discover relationships between data. Similar to biological neural networks, learning in ANNs is achieved through training processes using examples. In other words, the processing of input-output data involves repeatedly adjusting connection weights via the training algorithm until a convergence point is reached. ANNs can be described as structures composed of numerous simple processing units, each dealing with a part of a larger problem. In its simplest form, a processing unit multiplies the input by a set of weights, applies a non-linear transformation, and produces an output value. Artificial neural networks also possess the ability to generalize and work with incomplete data.[23]

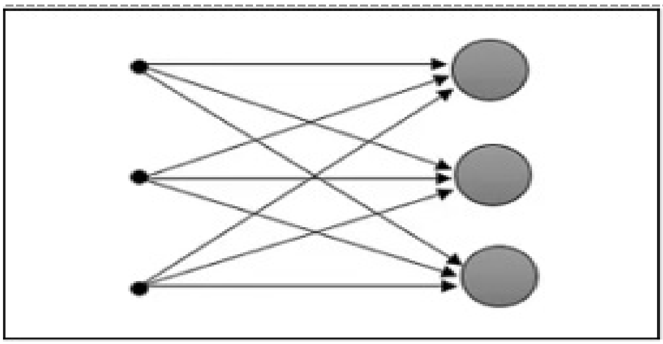

Figure 6. Artificial neural network

STUDIES ON THE USE OF ARTIFICIAL INTELLIGENCE IN AGE ESTIMATION

Hsieh et al.[24] (2007) developed a computer-based bone age estimation system by examining the geometric properties of the carpal bones of the hand. In this system, the bone age of children was categorized using four different classifiers (linear, nearest neighbor, backpropagation neural network, and radial basis function neural network). The study was based on a database of hand radiographs from 65 boys and 444 girls. The proposed normalization area ratio method was found effective in bone age classification, yielding results similar to the Greulich and Pyle atlas (**Figure 7**). The findings indicate that the discriminative power of bone area is high and that the evaluation of carpal bones can be accurately performed with neural networks. The bone age estimation was conducted using four different classifiers: linear classifier, nearest neighbor method, backpropagation neural network, and radial basis function neural network.[24]

Figure 7. Child hand graph example

Koitka et al.[25] (2020) developed a method in their studies that includes a detector network that identifies ossification areas in bone age estimation, along with gender- and region-specific regression networks that estimate age from these areas.

Deshmukh and Khaparde[26] (2022) developed a method based on a region-based convolutional neural network (R-CNN) model by considering the middle phalanx of the 3rd finger, third metacarpal, radius, and ulna regions of the hand (**Figure 8**).

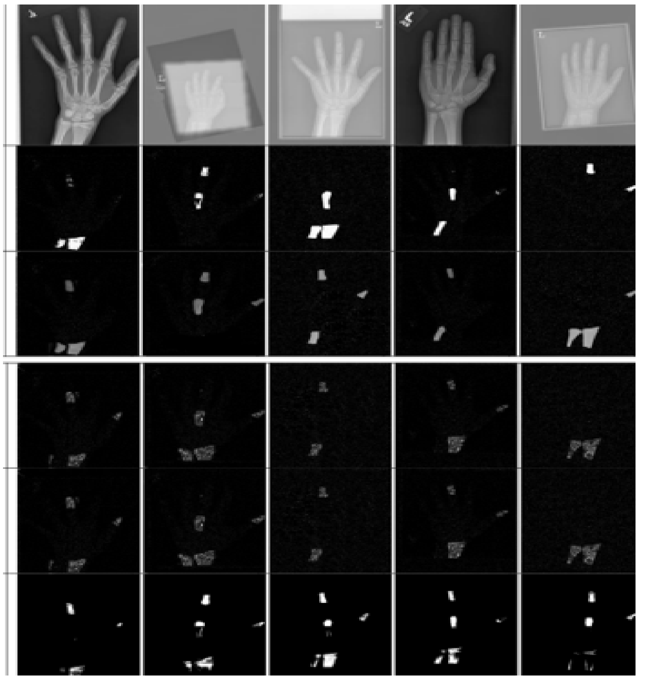

Figure 8. Bones used in Deshmukh and Khaparde's study

In the research by Demirel and Sonuç,[27] a local dataset containing left-hand radiographs of boys and girls aged 1-7 was used, and carpal bones were segmented through edge and contour detectors. The areas and the distal epiphysis region of the radius were loaded into the artificial neural network, and the accuracy rate of the age estimation obtained was determined to be 87%.

In their studies, Mohtarami et al.[28] evaluated the usability of facial angles (glabela and maxilla angles) obtained from tomography scans of a group consisting of 100 men and 100 women, along with data such as the length and width of the piriformis, in age estimation using ML algorithms, and the obtained accuracy rate was found to be 88% (**Figure 9**).

Çiftçi and Seçgin[29] retrospectively examined the foot radiographs of 341 individuals aged 8-65. Parameters such as the maximum width of the calcaneus, body width, maximum length, minimum length, facies articularis cuboidea height, and tuber calcanei width were measured from the radiographs, and participants were divided into three groups: 20-45 years, 46-64 years, and 65 years and older (**Figure 10**). The accuracy rate was determined to be 85%, leading to the conclusion that the calcaneus bone can be evaluated with high accuracy and sensitivity for age estimation.

Ataş and Özdemir[30] conducted a study using panoramic dental radiographs of 1332 individuals aged 8 to 68 to estimate forensic age, and using the InceptionV3 neural network, they achieved 87% accuracy in forensic age estimation. Narin and Yeniçeri[31] examined the hand and wrist radiographs of 388 boys and 387 girls aged 1-9 and calculated the ratio of bone tissue area to total hand and wrist area for each individual,

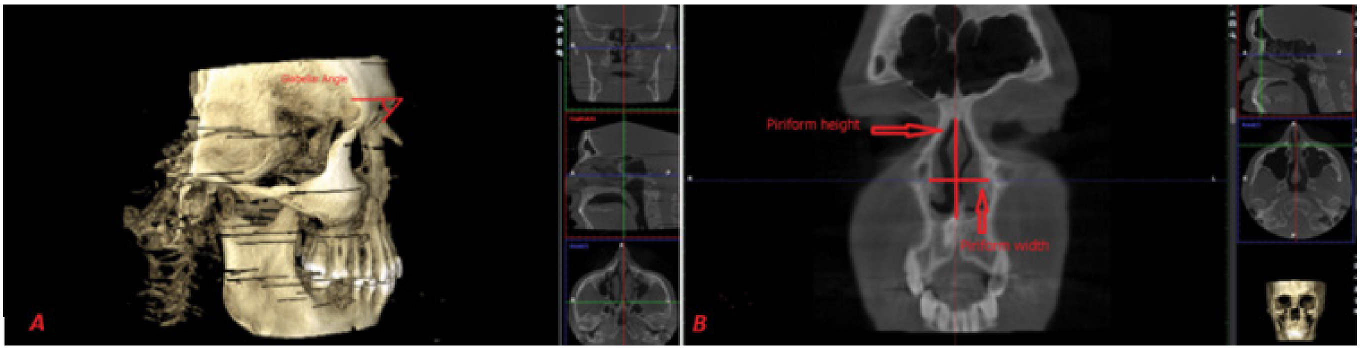

Figure 9. Glabella and piriform measurements used in the study by Mohtarami, Hedjazi and Manouchehri

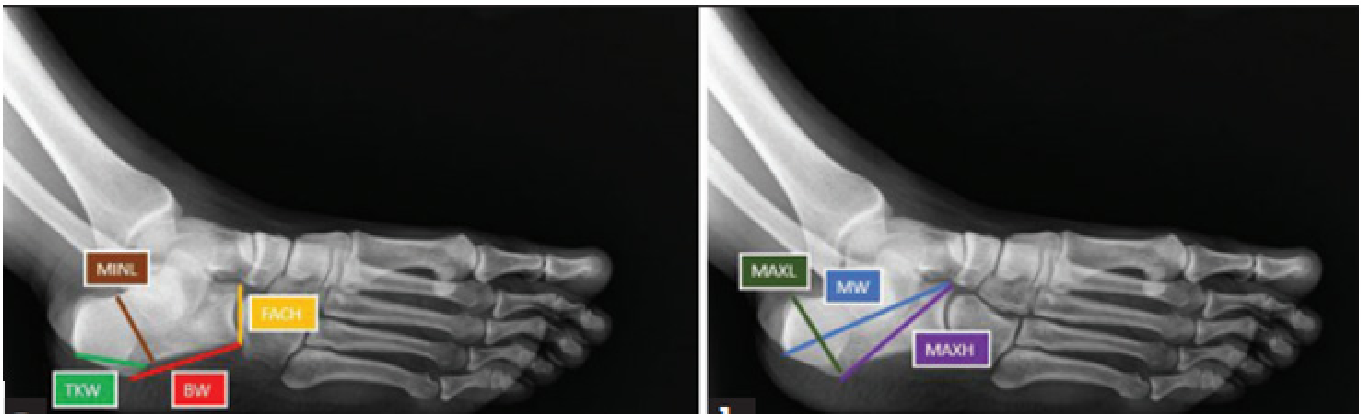

Figure 10. Foot bone parameters used in Çiftçi and Seçgin's study

classifying these data into three-month intervals. These data were accepted as a database, and the test data were compared with this database. Prediction models based on ML were used for bone age estimation, and age estimation was achieved with 95% accuracy using artificial intelligence.

Polat and Çelenk[32] conducted a study aimed at determining reliable, practical, and accurate methods for estimating dental age by examining the volumetric properties of teeth and pulp using three-dimensional images obtained through Cone Beam Computed Tomography.

Chen Fang et al.[33] focused on the use of DNA methylation in forensic genetics for determining chronological age in their research. The study suggested that microRNAs (miRNAs), a group of small non-coding RNAs, show a wide variability with age and could potentially be useful in age estimation. The study involved analyzing the expression profiles of miRNAs obtained from blood samples using large parallel sequencing methods. Age-related miRNAs were identified for age estimation, and seven different machine learning models were used to create age prediction models based on blood stains from individuals aged 20-69 years. The study reported an average error of 5.52 years for males and 7.46 years for females in age estimation.

CONCLUSION

Traditional methods and statistical analyses are frequently used in forensic age estimation; however, errors may occur in these studies due to factors such as data deficiencies, individual differences, and environmental influences, preventing the desired accuracy from being achieved. With the advancement of machine learning, artificial intelligence has become a critical tool in forensic age estimation. The developed algorithms, especially those using biometric data and image processing results, demonstrate that age estimation can be performed with high success rates and accuracy. Furthermore, AI has the potential to provide valuable insights into individuals' health status related to age estimation. These findings highlight the possibilities of AI in health assessment and age estimation.

The use of artificial intelligence in forensic age estimation increases the accuracy of the methods used and enables rapid results. The time-consuming and costly nature of traditional methods makes the application of AI in this field more appealing. To further develop AI applications, it is essential to diversify datasets, continuously update algorithms, and collect diverse data that include different ethnicities, genders, and age groups. This would help eliminate biases in AI systems and adopt a more universal approach. Additionally, attention to the privacy of health data and ethical considerations will enhance the reliability of AI applications.

In conclusion, artificial intelligence and machine learning have the potential to bring significant changes in forensic age estimation. This not only increases the efficiency of forensic systems but also provides more accurate and reliable information about individuals' health conditions.

ETHICAL DECLARATIONS

Referee Evaluation Process

Externally peer-reviewed.

Conflict of Interest Statement

The authors have no conflicts of interest to declare.

Financial Disclosure

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Author Contributions

All of the authors declare that they have all participated in the design, execution, and analysis of the paper, and that they have approved the final version.

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