Research Paper

Determining the Age Range Based on Machine-Learning Methods From Facial Skeletal Angles (Glabella and Maxilla Angle and Length and Width of Piriformis) in CT Scan

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Citation: Mohtarami SA, Hedjazi A, Haj Manouchehri R. Determining the Age Range Based on Machine-Learning Methods From Facial Skeletal Angles (Glabella and Maxilla Angle and Length and Width of Piriformis) in CT Scan. International Journal of Medical Toxicology and Forensic Medicine. 2022; 12(4):E38605. https://doi.org/10.32598/ijmtfm.v12i4.38605

https://doi.org/10.32598/ijmtfm.v12i4.38605

Article info:
Received: 10 Jun 2022
First Revision: 22 Jun 2022
Accepted: 27 Jun 2022
Published: 30 Nov 2022

Keywords:
Identification, Age estimation, Glabella angle, Maxillary angle, Piriformis length, Piriformis width, Machine learning, Artificial intelligence

ABSTRACT

Background: One of the main steps in identifying a person in forensic medicine is determining the age of skeletal remains, including the skull. This study aimed to investigate the possibility of predicting age from facial angles (glabella, piriformis, and maxillary angle and measuring peripheral length and width) with artificial intelligence in a CT scan.

Methods: The cross-sectional study method is simple random sampling using a questionnaire. Accurately measurable CT scan samples are selected. For exclusion criteria, gender uncertainty, and the possibility of measurement based on CT scan quality, the researchers examined the facial angles (angle of the glabella and maxilla and length and width of the piriformis) for 100 men and 100 women. The Mean±SD of the age was 39.16±2.22 years for men and 47.84±2.46 years for women. The samples were classified based on age differences, and then the data were analyzed using machine learning algorithms to determine the age group.

Results: After determining the exact amount of measurement, the data were evaluated by machine learning algorithms to determine the age group. Accordingly, in the age group classification based on the World Health Organization (WHO) (with an age difference of 10 years) (years±5) with 100% accuracy and in the second classification (with an age difference of 5 years) (years±2.5) with 88% accuracy and 79% precision of the age group was predicted.

Conclusion: The obtained data show the importance of new artificial intelligence methods, including machine learning, in providing new methods to determine age groups (age±2.5) through skull angles with high accuracy in cases where even cranial remains are found in identification in forensic medicine.

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1. Introduction

In forensic medicine, determining age and gender is essential in identifying two parameters. Sometimes, it is impossible to identify the victims due to severe injuries in mass incidents, such as earthquakes and floods, plane crashes, or the remains of corpses in mass graves. In such a situation, Hemogenetic or odontological methods are primarily used in such conditions [1-6].

Long bones, such as the femur, are formed by endochondral ossification, and facial bone is formed by intramembranous ossification. Different growth factors are influential in the formation of facial bones, but similar to long bones, bone density decreases with age. However, its specific ossification makes it unique [2].

Molecular genetic methods cannot always be studied due to different conditions, or a regular dental record is not available to people who want to be identified [3-7].

Identification studies using radio diagnostic imaging for body and skeletal remains and metric measurement methods for osseous structures are one of the most interesting new methods in this field [4-14].

Measuring bone dimensions (osteometric measurement) from radiological images has many advantages, such as no need to clean the bones and the possibility of measuring bones inside the soft tissue in examining the remains of the corpses [5-11].

Artificial intelligence is a broad branch of computer science that has been considered in medicine due to its problem-solving, decision-making, and pattern recognition capabilities. Machine learning, a subset of artificial intelligence, enhances the ability of computers to receive data and learn, manipulate algorithms, and organize the information they process. Research on machine learning of medical images holds great promise for medical researchers. Previous studies have shown the successful use of Machine Learning (ML) in classifying and diagnosing various diseases such as skin cancer at a functional level equal to or superior to that of specialists in the field [12, 13]

Pesaal's study was based on Lambros's theory about facial bone aging in 12 male participants who were divided into two groups based on age, based on the theory that the midface changes during aging in the form of a clockwise rotation in the sagittal plane relative to the base of the skull and elevation and the prominence of the glabellar angle are supported. In different age groups, the aging process causes changes in skeletal angles.

Classification is a machine learning method used to learn how to assign a class label to an input sample [14]. Each classification algorithm has its strengths and weaknesses. In other words, each classifier has a specific capacity to form the border between different classes. Classification can include two or more classes. Some classifiers like linear discriminant analysis (LDA), design a linear border between the classes, while other classifiers, such as K-Nearest Neighbor (KNN), support vector machine(SVM), random forest, and bagging can form a nonlinear border between the samples of classes [15].

KNN is one of the most widely used machine learning algorithms. It is a parameter-free algorithm (i.e. it has no assumptions about the data distribution) and lazy leaner (short learning time but long guessing time). First, when a test sample is put into the KNN classifier, its nearest neighbor, k, is determined. The label of the input sample is assigned to the label that receives the majority vote among the k labels of the closest sample. Furthermore, KNN has no training step, and its mechanism is open to interpretation. Another efficient statistical classifier widely used in low- and medium-scale applications is SVM; the kernel of SVM tries to map the inputs to a new high-dimensional space, in which the discrimination of samples in the new space is enhanced [16].

Decision Tree a tree has many analogies in real life, and it turns out that it has influenced a wide area of machine learning, covering both classification and regression. A decision tree can visually and explicitly represent decisions and decision-making in decision analysis. As the name suggests, it uses a tree-like model of decisions. Though it is a commonly used tool in data mining to derive a strategy to achieve a particular goal, it is also widely used in machine learning, which will be the main focus of this article [16].

Random forest, as its name implies, consists of many individual decision trees acting as an ensemble. Each individual tree in the random forest spits out a class prediction, and the class with the most votes becomes our model's prediction. It uses bagging and feature randomness when building each tree to create an uncorrelated forest of trees whose prediction by the committee is more accurate than any individual tree. In these tree structures, leaves represent class labels, and branches represent conjunctions of features that lead to those class labels [16, 17].

XGBoost is an open-source software library that implements optimized distributed gradient boosting machine learning algorithms under the Gradient Boosting framework [16, 17].

This study aimed to predict age from the globular and maxillary angles and length and width of the piriformis based on a CT scan with the help of artificial intelligence.

2. Materials and Methods

The study population after confirmation of the study in the forensic medicine organization, the research method in this study is cross-sectional. The gender and number of case files are in the questionnaire form. Sampling is by simple convenience sampling method. Stereotypes that can be accurately measured are selected, and exclusion criteria are gender uncertainty and the possibility of measurement according to the quality of the CT scan.

Three-dimensional (3D) CT images of skulls of 200 people, including 100 men and 100 women between the ages of 20 and 80, taken in the radiodiagnostic department of Mashhad University Medical Faculty for different indications between 2020 and 2021 were examined in the study.

We used two age group classifications in the classification First, according to the World Health Organization (WHO), groups 15-24 (y), 25-44 (y), 45-64 (y) and 65 ≤(y). In the second classification, with an age difference of 5 years, we divided the groups into twelve groups.

The desired parameters are measured through the digital tool in the one-dimensional image display program and recorded in the questionnaire.

Four parameters are measured in this study, which includes the following:

1- The glabellar angle between the reference line and the line drawn from the maximal prominence of the glabella to the nasofrontal suture (Figure 1-A).

2- The piriform height: Maximal height was measured from the lower rhinion to the anterior nasal spine (Figure 1-B)

3- The piriform aperture width: The widest distance between the left and right bone margin on the transverse plane was measured (Figure 1-B)

4- Left and right maxillary angles: Obtained on parasagittal slices at the level of the infraorbital foramen and mid-orbits (Figure 1-C)

The obtained measurements were evaluated with the SPSS software for Windows v. 21.0. Independent student's t-test was used to define the significance of the metric difference among sexes (P<0.05).

To analyze the age determination, the One-way analysis of variance (ANOVA) test was applied to the values obtained from both sexes, and the significance was evaluated among age groups.

In this study, first, the values of the facial angles) glabella and maxilla angle, and length and width of piriformis (were recorded by digital tools. Then, after loading data, preparation, and, Exploratory Data Analysis (EDA), the data were trained with the above classification methods, and the best forecasting method was obtained (Figure 2).

3. Results

In this study, the number of men was 200 people (50%), and the number of women was 200 people (50%). The mean age of the population in the study was detected as 34.50±17.08 for the whole population; 39.16±15.75 for men and 47.84±17.40 for women. In this study, a significant difference was not observed in comparing the mean age (P>0.05).

According to the t-test value obtained in evaluating the statistical significance of the difference between sexes, a significant difference was detected among sexes in glabella angle and maxillary angle, and piriform height. However, no significant difference was observed in piriform width. In glabella angle and maxillary angle measurements according to sex, it was detected that mean measurement values in women were higher than the mean measurement values in men. However, in measuring the width and length of the performance, it was more in men than women (Table 1).

The sex distribution of each group, including 50 males and 50 females in age groups with one of the age divisions of the WHO), was evaluated by One-way ANOVA analysis. A statistically significant difference was detected according to the One-way ANOVA test findings made according to the age groups for both sexes (P<0.05).

A post hoc test, including Tukey's b, was used to determine the mean difference between age groups between glablella angle and maxilla angle size. Only between the

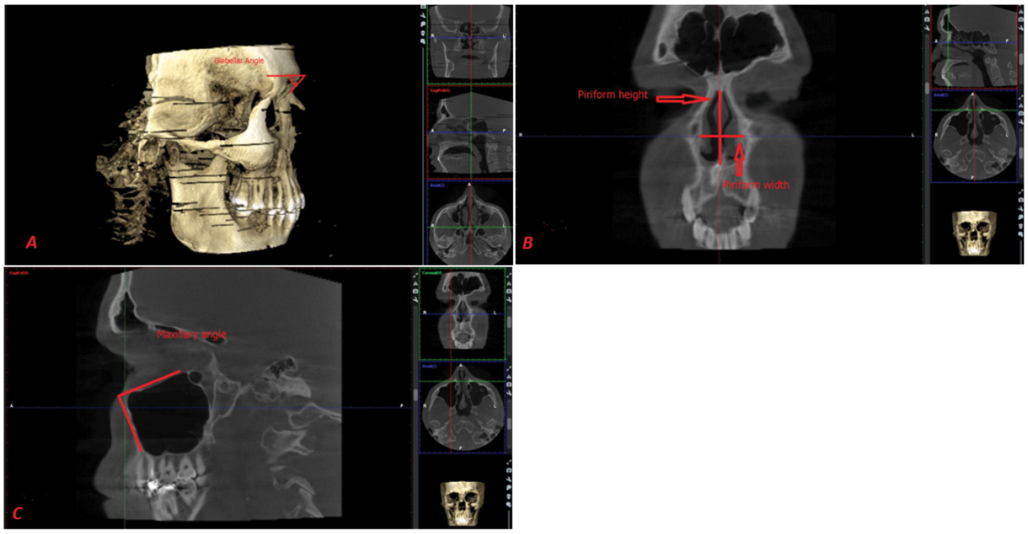

Figure 1. A. Glabellar angle between the reference line and a line drawn from the maximal prominence of the glabella to the nasofrontal suture.

Figure 1. B. The piriform height: maximal height was measured from below the rhinion to the anterior nasal spine and the piriform aperture width: the widest distance between the left and right bone margin on the transverse plane was measured

Figure 1. C. Left and right maxillary angles: Obtained on parasagittal slice at the level of the infraorbital foramen and mid-orbit

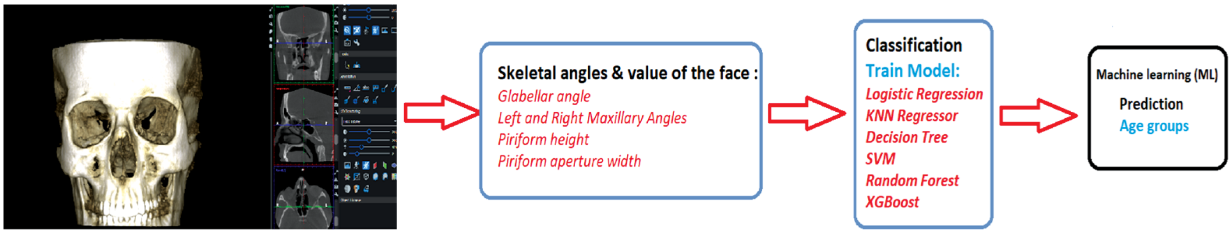

Figure 2. Block diagram of proposed approach.

Table 1. Analysis of male vs female

Measurement		Mean±SD		P
		Men	Women	
Angle, degrees	Glabellar	60.58±0.30	71.75±0.17	0.001
	Maxillary	78.90±0.68	79.10±1.90	0.001
Distance (mm)	Piriform width	25.04±0.49	24.84±1.15	0.5
	Piriform height	34.97±0.49	31.43±0.34	0.01

Table 2. Analysis of glabellar, maxillary angle, piriform width and piriform height by age distribution in both sexes

	Sex	Age Range (y)	Mean±SD	Min	Max	P			
Glabellar Angle (Degrees)	Male	15-24	62.50±0.12	62.3	62.7		0.000	0.000	0.000
		25-44	61.73±0.71	59.1	62.3	0.000		0.000	0.000
		45-64	57.80±0.52	57.0	57.5	0.000	0.000		0.285
		65≤	56.90±0.78	56.0	57.6	0.000	0.000	0.285	
	Female	15-24	73.41±0.26	73.2	74.0		0.041	0.000	0.000
		25-44	72.96±0.36	72.2	73.3	0.041		0.000	0.000
		45-64	71.16±0.54	70.4	72.8	0.000	0.000		0.000
		65≤	70.38±0.35	69.6	74.0	0.000	0.000	0.000	
Maxillary Angle (degrees)	Male	15-24	88.66±0.02	88.63	88.70		0.000	0.000	0.000
		25-44	88.17±0.32	87.60	88.60	0.000		0.000	0.000
		45-64	57.80±0.52	86.82	87.60	0.000	0.000		0.05
		65≤	56.90±0.78	86.70	86.80	0.000	0.000	0.05	
	Female	15-24	81.82±0.07	81.73	81.90		0.016	0.000	0.000
		25-44	81.21±0.55	79.60	81.70	0.016		0.000	0.000
		45-64	77.82±0.34	77.53	79.0	0.000	0.000		0.000
		65≤	77.33±016	77.10	77.50	0.000	0.000	0.000	
Piriform Height (mm)	Male	15-24	34.45±0.02	34.41	34.49		0.1	0.000	0.000
		25-44	34.75±0.25	34.50	35.40	0.1		0.000	0.000
		45-64	35.51±0.09	35.40	35.69	0.000	0.000		0.02
		65≤	35.33±0.05	35.80	35.91	0.000	0.000	0.02	
	Female	15-24	30.86±0.05	30.80	30.95		0.000	0.000	0.000
		25-44	31.13±0.10	31.00	31.37	0.000		0.000	00.000
		45-64	31.63±0.10	31.40	31.77	0.000	0.000		0.001
		65≤	31.78±0.01	31.77	31.81	0.000	0.000	0.001	
Piriform Width (mm)	Male	15-24	24.53±0.04	24.50	24.60		0.000	0.000	0.000
		25-44	24.83±0.08	24.67	25.00	0.000		0.000	0.000
		45-64	25.45±0.28	25.13	25.90	0.000	0.000		0.000
		65≤	26.14±0.21	24.94	26.40	0.000	0.000	0.000	
	Female	15-24	23.14±0.09	23.00	23.30		0.15	0.000	0.000
		25-44	23.67±0.37	23.30	24.60	0.15		0.000	0.000
		45-64	25.53±0.35	24.80	25.88	0.000	0.000		0.000
		65≤	26.02±0.17	25.89	26.40	0.000	0.000	0.000	

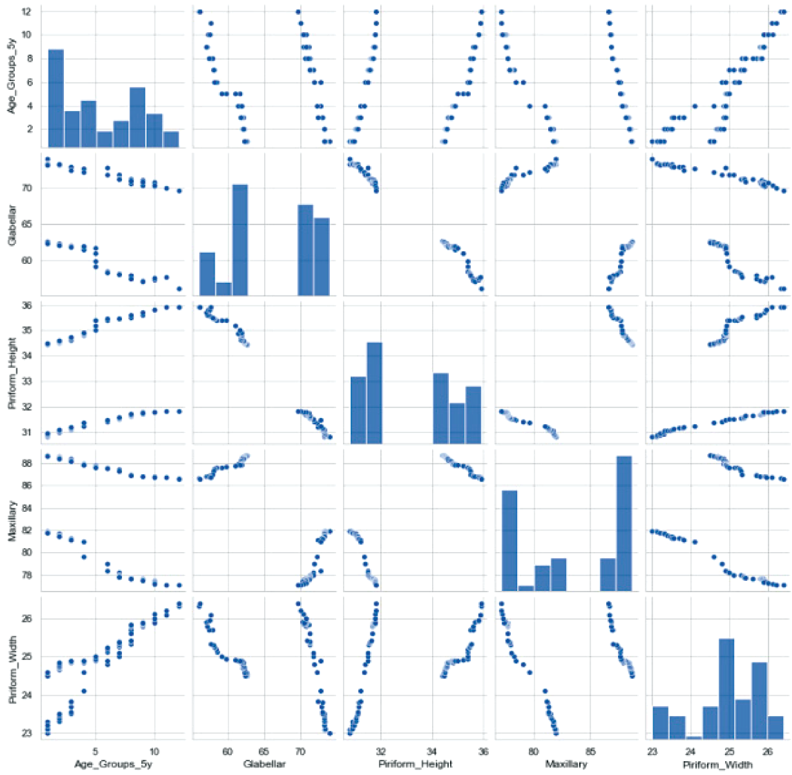

Figure 3. Distribution of variables by aage group with a difference of 5 years

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age groups of men aged 45-64 years and those over 65 years, no significant differences were observed. However, in the female group, no significant difference was observed between the age group of 15-24 and the age group of 44-24 (Table 2).

In the piriform height, no significant relationship is observed between the age group of men between 15-24 and 25-44 years and between the age group of 45-64 years and equal age and more than 65 according to Scheffe's test. In women, a significant difference is observed between all age groups (Table 2).

In the piriform width, a significant difference is observed between all age groups of men. No significant difference is observed between the age groups in women according to the ANOVA test, between the age group of 15-24 and the age group of 25-44 (Table 2).

In forensic medicine, an attempt is made to determine the age as accurately as possible from the skeletal re-

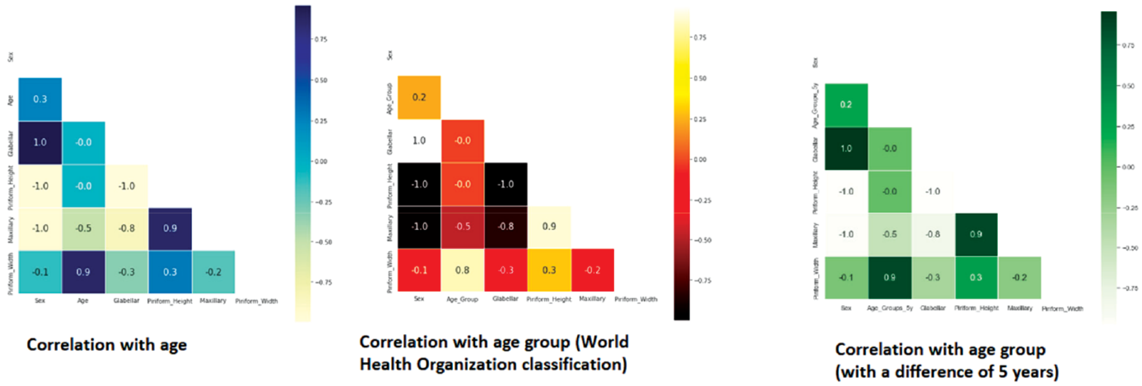

Figure 4. Correlation table

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Table 3. A classification report

Age Groups (y)	Model	%			
		Accuracy	Precision	Recall	F1-Score
According to the WHO 15-24 25-44 45-64 65≤	Logistic regression	68	79	59	61
	SVM	88	86	84	85
	Decision Tree	88	90	85	85
	KNN regressor	96	97	94	95
	Random forest	100	100	100	100
	XGBoost	100	100	100	100
Age±2.5 (y) 15-24 25-29 30-34 35-39 40-44 45-49 50-54 55-59 60-64 65-69 70-74 75-79	Logistic regression	36	22	32	25
	SVM	60	47	48	47
	KNN regressor	72	56	65	58
	KNN by best error rate	76	62	72	66
	Decision tree	76	73	70	65
	Random forest	84	77	78	74
	XGBoost	88	79	82	86

WHO: World Health Organization; SVM: Support vector machine; KNN: k-nearest neighbor

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mains of the skull. Therefore, for this purpose, we divided the age groups into 12 groups with a difference of five years (Age±2.5).

The first step in any attempt to analyze or model data is to understand how the variables are distributed. Distribution visualization techniques can provide quick answers to many vital questions.

Data visualization is a critical player in data science. They are influential in exploring variables and the relationships between them. Data visualization is much preferred over simple numbers to present results and findings. In Figure 3, we show the distribution of facial angle variables by age group with a difference of 5 years.) Figure 3).

In this study, we reviewed and analyzed the data (prepare data and exploratory data analysis [EDA]). Correlation table Two-way table of relationships between correlations. The row titles are the scores of one variable and the column headings are the scores of the second variable, and a cell indicates how many times the row score is related to it. This study investigated the relationship between age and age groups with facial bone angles. Positive coefficients increase the log odds of the response (and thus increase the probability), and negative coefficients decrease the log odds of the response (and thus decrease the probability) (Figure 4).

Machine learning algorithms: (Model, predict, and solve)

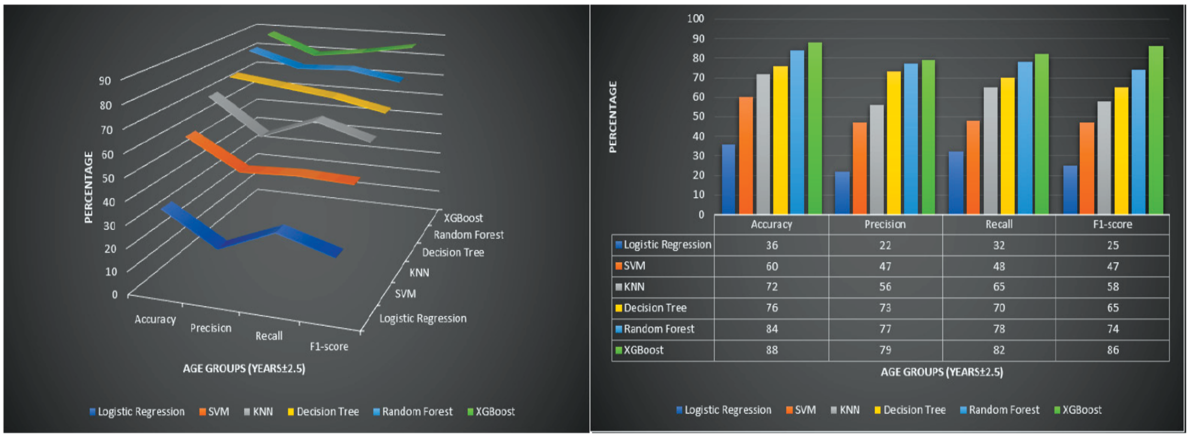

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Figure 5. Comparsion of learning machine algorithms in classification with 5 years differences (years±2.5)

Considering the problem and the need to use new solutions, including machine learning algorithms, we will examine some models of predictive modeling algorithms for evaluation. According to our understanding of the problem, the structure and distribution of data, the number of classes, and the time complexity of building the model, among more than 60 existing algorithms, we are limited to a few selected models. Our problem is a classification and regression problem. We want to identify the relationship between output (age groups) with other variables or features (gender, glabella, maxilla angle, and length and width of piriformis).

In this research, machine learning is a type of supervised learning because it works by importing data sets that include special features in terms of the size of bone parameters and target features. The supervised learning algorithm obtains the relationship between the training examples and their specific target variables, and it uses the learned relation to classify completely new inputs (without targets). We can limit our choice of models to a few models.

These include:

Logistic regression

KNN or k-nearest neighbors

Support vector machines (SVM)

Decision tree

Random forrest

XGBoost

In this study, the scikit-learn model (version 0.24.2) was performed in the Python programming language (version 3.7.1). Machine Learning (ML) modeling was done using Google Colab. Logistic regression (LR), KNN regressor, Decision Tree (DT), Random Forest (RF), SVM, and XGBoost were used. The data set was mixed by mixing, and the first 75% was designated as the training set, while the last 25% was designated as the experimental set.

Validation

Validation of the results was performed with the following statistical evaluation criteria including accuracy, sensitivity, and specificity as well as the Confusion matrix. The items were calculated according to the following formulas [18-20].

- TN=True negative
- FP=False positive
- FN=False negative
- TP=True positive
- Accuracy=(TP+TN)/(TP+TN+FP+FN)
- Precision=TP/(TP+FP)
- Sensitivity (Recall)=TP/(TP+FN)
- Specificity (TNR)=TN/TN+FP ---------------- à True negative rate

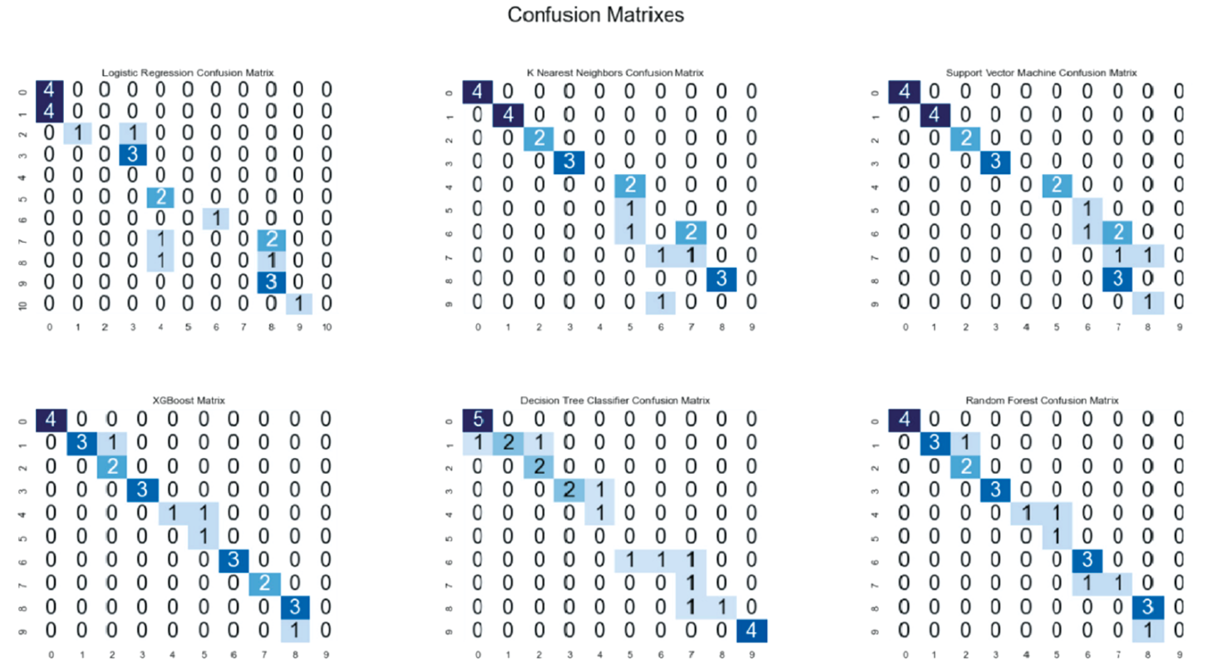

Figure 6. Confusion matrix for the age group with an age difference of 5 years.

In this study, we have a confusion matrix, which is a matrix that plots the value of correct predictions against the value of false predictions.

We also used -Score F1 in this paper. This score acts as a harmonic mean of accuracy and recall, and when it is equally important to avoid both false positives and false negatives.

F1-Score=2×(precision*recall)/(precision+recall)

Model evaluation

Now, we can rank our evaluation of all models to choose the best model for our problem. While in age groups according to WHO, both XGBoost and random forest score the same, we use random forest because it corrects XGBoost's habit of overfitting its training set. In the 5-year age group, the best accuracy was 88%, and the best precision was 79% for XGBoost.

The classification report is a measure of machine learning performance used to demonstrate accuracy, recall, F1 score, and support for the trained classification model. In our study, it is shown in Table 3 (Figure 5).

A confusion matrix is a table used to define a classification algorithm›s performance. A confusion matrix visualizes and summarizes the performance of a classification algorithm (Figure 6).

4. Discussion

Identification is one of the crucial topics in forensic medicine and the discussion of bone changes caused by age and sex in all bones, including facial bones, is one of the topics considered for a long time. The areas most affected by reduced skeletal to those areas of the face that manifest the most prominent stigmata of aging [10]. Changes in the size of the facial bones are not the result of bone atrophy but the result of bone resorption [11].

In this study, we apply a new method based on machine learning. We performed the classification program of the main subgroups of age groups in two ways: the first method is based on the classification of the WHO, and the second method is based on age groups with a difference of 5 years. Predictive results can vary when performed by forensic experts. This variation stems from two main factors: differences in individual-to-individual measurements and the potential impact of limited data. Under these conditions, machine learning-based models can make more accurate measurements and reduce the variability between observers.

A comprehensive search on Web of Science, Scopus, and Google shows no publication on using computer science techniques based on skull angles to predict age groups. However, artificial intelligence techniques allow you to process images and differentiate them for classification purposes.

Table 3 presents that when the age is obtained according to the age group classification of the WHO, the accuracy rate ranges from the lowest value of 68% to 100%. However, this classification is worthless given the 10-year gap in forensics. Therefore, in this article, we created an age group with a difference of 5 years, and then skull angles were used to determine the age in this group. The results of the experimental group in this paper showed high accuracy when using the XGBoost library (Table 3 and Figure 4).

This study aimed to predict the age group from the skull's angles (glabella and maxilla angle and length and width of piriformis) using CT images. It was analyzed whether the bone is immature and may change with age.

In this study, the mean age of the population was 34.50±17.08 for the whole population, 39.16±15.75 for men, and 47.84±17.40 for women. The age range was between 20 and 78 years in men and between 20 and 76 years in women. In the male group, 95% of the subjects were aged between 34.68 and 43.63 years, and in the female group, 95% were aged between 42.84 and 52.78 years. In the study by Kim et al., 223 facial CT scans were analyzed (108 men, 115 women). The age of the subjects ranged from 20 to 81 years [18]. In Robert's study, the mean age in the "young" age group was 29.9 years for men and 27 years for women. The men in our "middle" age group had a mean age of 54.5 years, whereas the women had a mean age of 51. The mean age in the "old" age group was 76 years for men and 70 years for women, which was similar to the range in this study [21].

Based on one of the divisions of the existing age groups in the WHO, four age groups were studied and compared between men and women. The age group of 25-44 years with 40% was the most studied the age groups of 45-64 years with 31%, the age group over 65 years and more with 15%, and the age group of 15-24 years with 14%, respectively. The researchers of this study are on this basis that in this division, the groups are divided into four groups, young, middle-aged, adult, and old. This division was selected for data analysis due to significant changes in facial bones in these four age groups and the importance of this age range in legal issues and identification which was similar to the division of Mendelson et al.'s study [8]. The highest frequency in this study was in the age group of 25-44 years, which was similar to the frequency of Kim et al.'s study [18].

In our study, no significant difference was observed between the age groups of men in the age group of 45 years and older in men, but a difference was observed between the young and middle-aged age groups in this study, and different results were obtained in the age group of women. No significant difference existed between young and middle age groups, but a significant difference existed between adult and elderly age groups. The reason for this can be explained by Knight's book that in women, the skull shape of the forehead is longer and more vertical and has retained prominence from childhood more than the skull of men. The results of this study were similar to those of Richard et al. and also different from the results of the Kim study, which reported a significant difference in adulthood for men but no significant difference in old age for women [9, 18].

In the study, a significant difference was observed in the mean size of the maxillary angle between men and women in this study. In the study of Boris et al., no significant relationship was observed between the size of the right and left maxillary angles in both sexes. We used a 3D CT-scan, but Boris's measurements were based solely on a 2D CT scan. Also, in the study of age groups, no significant difference was observed between the age groups of 65-45 and more and equal to 65 in the men's group. Other age groups have a significant difference in the mean value. In this study, no significant difference was observed between women in the age group of 24-24 and the age group of 25-44. However, among other age groups, according to Table 2, a significant difference was observed in the size of the maxilla angle in the measurement in this study. The results of this study were similar to the results of Jim et al. in the study of age groups. However, we used the differentiation of age groups into bisexuals in maxillary size, which increased the accuracy of our results in evaluating this parameter [18, 22].

No significant difference was observed between age groups in men except for one group, which was similar to David's results among age groups [23]. However, in females, in this study, a significant relationship was observed between all groups, which indicates the stages of development in all periods in the condition of the bone in the growth of the midface in females. Kahan's results also showed this research.

5. Conclusion

Given that no guidelines were available for determining age based on CT scans, this study was performed to investigate the use of 3D CT scans to help identify the age group. A step towards using radiographic images and CT scans in the future as an alternative to autopsy in identification or as a paraclinical tool in various identification processes in forensics.

In this study, we selected four angles of the face, which in the studies of other researchers indicate that the spherical and maxillary angles change in men and women with age. Then we taught artificial data intelligence with the help of machine learning algorithms. Using machine learning, we determined the age of 2.5 years with an accuracy of 88%.

Ethical Considerations

Compliance with ethical guidelines

The Ethics Committee of the Iranian Legal Medicine Organization approved this study (Code: IR.LMO.REC.1399.003). The written informed consent form has been obtained from patients or their legal guarantees.

Funding

This article was supported by the Iranian legal medicine organization.

Authors' contributions

All authors contributed to the preparation of this article.

Conflict of interest

The authors declared no conflict of interest.

Acknowledgements

We appreciate the support of the Iranian legal medicine organization.

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