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Sex and age estimation with machine learning algorithms with parameters obtained from cone beam computed tomography images of maxillary first molar and canine teeth

Deniz Senol[1*], Yusuf Secgin[2], Burak Suayip Duman[3], Seyma Toy[2] and Zulal Oner[4]

Abstract

Background The aim of this study is to obtain a highly accurate and objective sex and age estimation by using the parameters of maxillary molar and canine teeth obtained from cone beam computed tomography images in the input of machine learning algorithms. Cone beam computed tomography images of 240 people aged between 25 and 54 were randomly selected from the archive systems of the hospital and transferred to Horos Medikal. 3D curved multiplanar reconstruction was applied to these images and a 3D image was obtained. The resulting image was brought to the orthogonal plane and the measurements were made by superimposing them.

Results The results were grouped in four different age groups (25–30, 31–36, 37–49, 50–54) and recorded. As a result of our study, the highest accuracy rate was found as 0.81 in sex estimation with ADA Boost Classifier algorithm, while in age estimation, the highest accuracy rate was found as 0.84 between 25–30 and 31–36 age groups with random forest algorithm, as 0.74 between 25–30 and 37–49 age groups with random forest and ADA Boost Classifier algorithms and as 0.85 between 25–30 and 50–54 age groups with random forest algorithm.

Conclusions Our study differs from other studies in two aspects; the first is the selection of a sensitive method such as cone beam computed tomography, and the second is the selection of machine learning algorithms. As a result of our study, the highest accuracy rate was found as 0.81 in sex estimation and as 0.85 in age estimation with parameters of maxillary canine and molar teeth.

Keywords Sex estimation, Age estimation, Cone beam computed tomography, Machine learning algorithms, Maxillary canine and molar teeth

*Correspondence:
Deniz Senol
denizanatomi@gmail.com
[1] Department of Anatomy, Faculty of Medicine, Düzce University, Düzce, Turkey
[2] Department of Anatomy, Faculty of Medicine, Karabük University, Karabük, Turkey
[3] Department of Oral Diagnosis and Radiology, Faculty of Dentistry, İnönü University, Malatya, Turkey
[4] Department of Anatomy, Faculty of Medicine, İzmir Bakırçay University, İzmir, Turkey

Background

Sex and age estimation of individuals has an important place in forensic anthropology, forensic odontology and forensic medicine studies. Sex and age estimation both facilitate and accelerate identification of individuals; therefore, while sex is the first biomarker sought in forensic studies, the second one is age (Capitaneanu et al. 2017; Pereira et al. 2020).

Skull, pelvis, sternum, phalanx, patella, and mandible bones are used in forensic studies (Oner et al. 2019; Senol et al. 2022; Toy et al. 2022; Turan et al. 2019). However, teeth, mandible, and maxilla are also frequently preferred. Due to their compact structure and the fact that they are surrounded by facial muscles, teeth are among the structures that preserve their integrity for a long time after death. Thanks to this compact structure, teeth come to the forefront in cases such as fire and war when the body integrity is impaired (Narang et al. 2014).

Age estimation is critically important not only in postmortem cases, but also in living individuals. Especially after the 2000s, it has been used in criminal cases to estimate the age of individuals who do not want to tell their real age, or in civil cases to estimate the exact age of individuals who want to learn their full age (Azevedo et al. 2015).

Although genetic, histological, radiological, and biochemical methods are used in forensic analyses, most of these are not economical and fast. Radiological methods are widely used both because they are fast and economical and also because they allow for segmentation. Of these radiological methods, computed tomography (CT) stands out with its widespread use (Alias et al. 2018; Nayar et al. 2017).

Machine learning algorithm (ML) is an engineering based method that can give more objective and better results than classical methods and it has begun to be used in the field of health today (Erickson et al. 2017; Rajkomar et al. 2019). Logistic regression (LR) is an extension of ordinary regression analysis and it is a strong classification algorithm that can model which class the data belongs to. Decision tree (DT) is a strong, old, quick-to-learn, and easy to interpret tree algorithm that classifies data with a structure similar to tree. Random forest (RF) is an ML algorithm with a feature that classifies ensembles consisting of multiple tree structures (Uddin et al. 2019). Linear discriminant analysis (LDA) is an advanced version of principal component analysis and it is frequently preferred in the classification of linear data. Quadratic discriminant analysis (QDA) is a version of LDA used in non-linear data and it is more flexible than LDA (Jeng et al. 2020). AdaBoost classifier (ADA) is an iterative ensemble classifier algorithm that analyzes data by combining classifiers. Extra tree classifier (ETC) is a classification algorithm that generates pruned decision trees by forming random cut off points (Khan and Ramsahai 2021).

The aim of this study was to obtain highly accurate and objective results by using ML with parameters obtained from CTs of maxillary molar and canine teeth.

Methods

Study population

This study was conducted with the 2020/1099 numbered decision of non-interventional local ethics committee. Study population included 120 female and 120 male individuals between the ages of 25 and 54 who did not have any pathologies or interventional operation in maxillary tooth structure. The individuals included in the study were grouped in 4 different age groups as 25–30, 31–36, 37–49, 50–54 years of age.

Cone beam computed tomography (CBCT) scanning protocol

NewTom 5G CBCT device (Verona, Italy) was used to obtain CBCT images with the following parameters: 110 kVp, 1–11 mA, 3.6 s. Images containing artifacts that prevent segmentation (metal artifact, artifacts caused by position errors during shooting, etc.) were excluded from the study.

Image processing

The images in Digital Imaging and Communications in Medicine (DICOM) format taken from Picture Archiving Communication Systems (PACS) of our hospital were transferred to personal work station Horos Medical Image Viewer (Version 3.0, USA) program. Axial, coronal and sagittal plane images were obtained by applying 3D curved multiplanar reconstruction (MPR) to transferred images (Fig. 1). The line passing through the pars maxillaris of palatum durum on the images of three planes obtained were determined and all images were brought to the orthogonal plane. These images brought to orthogonal plane were overlapped and length, angle, and curvature length measurements were performed (Fig. 2).

Measurement parameters are as follows:

- ✓ The distance between canine teeth (CT-L)
- ✓ The angle of canine teeth to posterior nasal spine (PNSCT-A)
- ✓ The angle of canine teeth to incisive foramen (IFCT-A)
- ✓ The distance of right canine tooth to first molar (FMRCT-L)
- ✓ The distance of left canine tooth to first molar (FMLCT-L)
- ✓ The angle of first molar to posterior nasal spine (PNSFM-A)
- ✓ The angle of first molar to incisive foramen (IFFM-A)
- ✓ Curvature length of the right first molar (RFM-CL)
- ✓ Curvature length of the left first molar (LFM-CL)
- ✓ The distance between the first molars (FM-L)
- ✓ The distance between the right first molar and third molar (RFMTM-L)
- ✓ The distance between the left first molar and third molar (LFMTM-L)
- ✓ Right molar angle (RM-A)

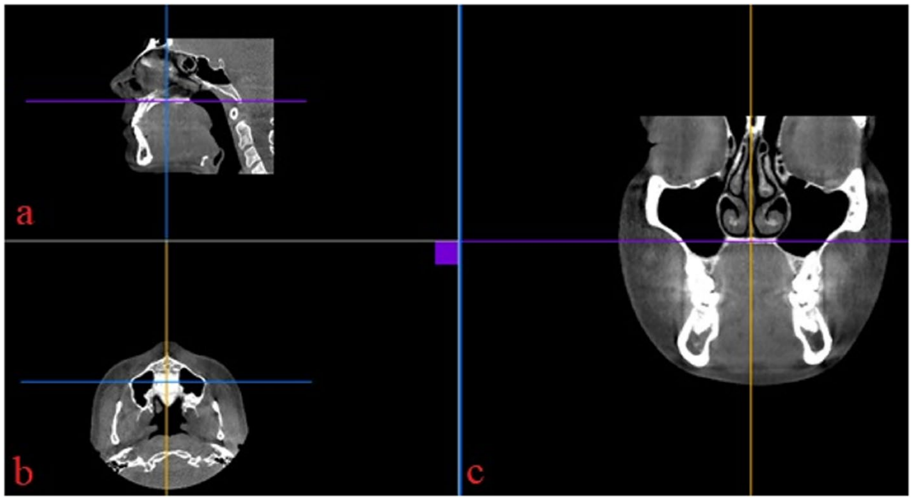

Fig. 1 Demonstration of the process of bringing to orthogonal plane (**a**: sagittal, **b**: coronal, **c**: axial)

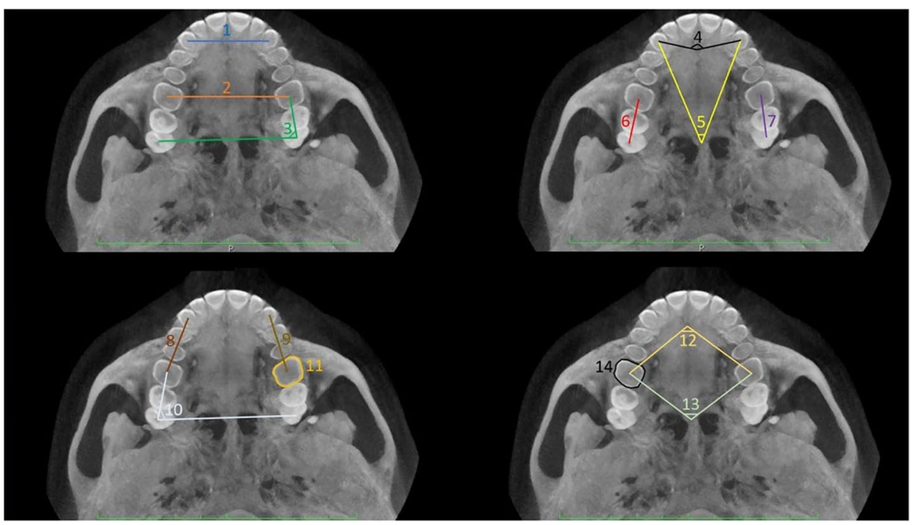

Fig. 2 Demonstration of measurements (1 CT-L, 2 FM-L, 3 LM-A, 4 IFCT-A 5 PNSCT-A, 6 RFMTM-L, 7 LFMTM-L, 8 FMRCT-L, 9 FMLCT-L, 10 RM-A, 11 LFM-CL, 12 IFFM-A, 13 PNSFM-A, 14 RFM-CL)

✓ Left molar angle (LM-A)

Machine learning algorithm application

Python programming language (Version 3.7.1) and scikit-learn framework (Version 0.20.0) were used for ML modelling. Modelling was performed by using a computer with Hp-Folio 1040 model, i7 operating system and 8 Gb Ram. In algorithms, training set was determined as 80%, while the test set was determined as 20% and logistic regression (LR), decision tree (DT), linear discriminant analysis (LDA), AdaBoost classifier (ADA), quadratic discriminant analysis (QDA), extra tree classifier (ETC), random forest (RF) algorithms were preferred. Algorithms were applied in 25–30 vs 31–36, 25–30 vs 37–49, 25–30 vs 50–54 age groups and between sexes. In our study, age groups were divided into many different combinations and used as input in algorithm analysis. Among these combinations, those with an Accurucy (Acc) ratio above 0.70 were included in the study. Other combinations provided Acc ratio between 0.50 and 0.70. The factors affecting the accuracy rate can be briefly shown as the number of individuals, the fact that the teeth structure of the individuals does not show values in their own age group, the age of the individual is very close to another age group. In order to eliminate the negativity due to closeness between age groups, individuals can be divided into months, weeks and days, not years, but this requires a huge number of individuals. This will adversely affect situations where quick decisions are required. For this reason, year classification was preferred in our study. Acc, specificity (Spe), sensitivity (Sen), and F1 score (F1) values were used as performance criteria. These performance criteria obtained for sex and age estimation belong to the test set and the training set was used for learning algorithms.

$$\mathrm{Acc} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN} + \mathrm{FP} + \mathrm{TN}}$$

$$\mathrm{Sen} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$\mathrm{Spe} = \frac{TN}{TN + FP}$$

$$F1 = 2\frac{Spe \times Sen}{Spe + Sen}$$

Equation 1 (FP; false positive, FN; false negative, TP; true positive, TN; true negative).

In order for the results obtained to reflect the truth, no extraction or cleaning was performed in the entire data set. In addition, tenfold cross-validation was applied in our study and the Acc value of each algorithm was given as mean ± standard deviation. In our study, the contribution of the parameters to the overall result was revealed by using the SHAP analyzer of the RF algorithm.

Statistical analysis

Two hundred forty individuals and 14 parameters were used in the present study; median, minimum and maximum values were included in the descriptive statistics for each age group of the parameters. Descriptive statistics were performed by using Minitab 17 statistics program.

Results

Mean age of the men in the study were found as 39.29 ± 10.98, while mean age of the women was found as 39.11 ± 10.60 and no significant difference was found between ages in terms of sex ($p \geq 0.05$). Of the 240 individuals whose images were evaluated in the study, measurement results of 72 individuals between the ages of 25 and 30 are shown in Table 1. Median value of men was found as 25, while median value of women was found as 26 in terms of sex.

Of the 240 individuals whose images were evaluated in the study, measurement results of 24 individuals between the ages of 31 and 36 are shown in Table 2. Median value of men was found as 36, while median value of women was found as 36 in terms of sex.

Of the 240 individuals whose images were evaluated in the study, measurement results of 84 individuals between the ages of 37 and 49 are shown in Table 3. Median value of men was found as 40, while median value of women was found as 43 in terms of sex.

Of the 240 individuals whose images were evaluated in the study, measurement results of 60 individuals between the ages of 50 and 54 are shown in Table 4. Median value of men was found as 53, while median value of women was found as 53 in terms of sex.

In the estimation of 25–30 vs 31–36 age groups, the highest Acc rate was found as 0.84 with RF algorithm. In the estimation of 25–30 vs 37–49 age groups, the highest Acc rate was found as 0.74 with RF and ADA algorithms.

Table 1 Descriptive statistics of individuals between the ages of 25 and 30

Parameters	Sex	Median	Minimum	Maximum
Age (years)	Male	25.00	21.00	30.00
	Female	26.00	22.00	30.00
CT-L (cm)	Male	3.19	2.19	3.65
	Female	3.06	2.27	3.52
PNSCT-A (°)	Male	41.66	35.42	53.01
	Female	42.39	33.16	51.08
IFCT-A (°)	Male	164.65	122.00	179.76
	Female	164.16	123.40	179.66
FMRCT-L (cm)	Male	2.28	1.62	2.59
	Female	2.21	1.76	2.50
FMLCT-L (cm)	Male	2.29	1.48	2.79
	Female	2.18	1.43	3.02
PNSFM-A (°)	Male	96.70	88.72	133.40
	Female	98.42	84.78	118.24
IFFM-A (°)	Male	105.75	86.67	125.55
	Female	98.85	81.93	109.18
RFM-CL (cm)	Male	3.39	2.63	3.99
	Female	3.44	2.90	4.11
LFM-CL (cm)	Male	3.39	2.86	4.06
	Female	3.38	2.96	4.36
FM-L (cm)	Male	4.69	4.21	5.33
	Female	4.45	3.73	4.87
RFMTM-L (cm)	Male	1.88	1.31	2.57
	Female	1.56	1.12	2.31
LFMTM-L (cm)	Male	1.93	1.00	2.74
	Female	1.57	1.10	2.34
RM-A (°)	Male	82.27	60.10	118.09
	Female	76.36	60.64	92.64
LM-A (°)	Male	87.72	53.21	110.55
	Female	78.26	58.86	95.42

Table 2 Descriptive statistics of individuals between the ages of 31 and 36

Parameters	Sex	Median	Minimum	Maximum
Age (years)	Male	36.00	31.00	36.00
	Female	36.00	31.00	36.00
CT-L (cm)	Male	3.32	2.89	3.73
	Female	3.12	2.59	3.33
PNSCT-A (°)	Male	44.40	34.63	54.75
	Female	45.19	40.52	49.03
IFCT-A (°)	Male	167.57	132.00	178.52
	Female	144.20	144.20	173.91
FMRCT-L (cm)	Male	2.31	1.85	2.59
	Female	2.22	1.66	2.52
FMLCT-L (cm)	Male	2.30	1.83	2.61
	Female	2.18	1.66	2.33
PNSFM-A (°)	Male	103.36	68.77	146.33
	Female	101.22	91.53	115.41
IFFM-A (°)	Male	97.29	91.64	149.52
	Female	100.25	97.14	113.99
RFM-CL (cm)	Male	3.40	2.33	4.57
	Female	3.53	2.53	4.02
LFM-CL (cm)	Male	3.33	2.37	4.56
	Female	3.54	2.78	3.91
FM-L (cm)	Male	4.81	4.02	5.48
	Female	4.72	3.61	4.85
RFMTM-L (cm)	Male	1.89	1.21	2.19
	Female	1.73	1.24	1.92
LFMTM-L (cm)	Male	1.84	1.17	2.38
	Female	1.50	1.06	2.12
RM-A (°)	Male	86.56	72.01	118.52
	Female	72.52	68.28	95.23
LM-A (°)	Male	83.04	64.89	100.69
	Female	81.72	63.36	99.35

Table 3 Descriptive statistics of individuals between the ages of 37 and 49

Parameters	Sex	Median	Minimum	Maximum
Age (years)	Male	40.00	37.00	49.00
	Female	43.00	38.00	49.00
CT-L (cm)	Male	3.18	2.88	3.94
	Female	3.09	2..36	3.63
PNSCT-A (°)	Male	40.41	33.81	54.65
	Female	43.00	36.87	56.38
IFCT-A (°)	Male	159.15	127.27	179.87
	Female	164.37	129.79	179.84
FMRCT-L (cm)	Male	2.23	1.65	2.91
	Female	2.13	1.57	2.67
FMLCT-L (cm)	Male	2.25	1.66	3.17
	Female	2.22	1.52	2.60
PNSFM-A (°)	Male	92.03	74.16	134.50
	Female	98.95	74.94	129.45
IFFM-A (°)	Male	102.41	82.12	128.32
	Female	103.02	80.27	118.08
RFM-CL (cm)	Male	3.38	2.67	3.99
	Female	3.28	2.39	3.93
LFM-CL (cm)	Male	3.39	2.39	4.37
	Female	3.16	2.19	3.88
FM-L (cm)	Male	4.80	4.29	5.70
	Female	4.58	3.93	5.24
RFMTM-L (cm)	Male	1.94	1.02	2.41
	Female	1.75	1.19	2.25
LFMTM-L (cm)	Male	1.80	1.13	2.50
	Female	1.76	1.20	2.11
RM-A (°)	Male	79.27	66.06	105.60
	Female	80.20	65.06	97.36
LM-A (°)	Male	82.44	67.19	107.89
	Female	82.31	69.86	100.77

The highest Acc rate of 25–30 vs 50–54 age groups was found as 0.85 with RF algorithm. In total sex comparison, the highest Acc rate was found as 0.81 with ADA algorithm (Table 5).

In the estimation of 25–30 vs 31–36 age groups, the highest Spe rate was found as 0.87 with RF algorithm. In the estimation of 25–30 vs 37–49 age groups, the highest Spe rate was found as 0.75 with RF and ADA algorithms. The highest Spe rate of 25–30 vs 50–54 age groups was found as 0.85 with RF algorithm. In total sex comparison, the highest Spe rate was found as 0.81 with ADA algorithm (Table 6).

In the estimation of 25–30 vs 31–36 age groups, the highest Sen rate was found as 0.84 with RF algorithm. In the estimation of 25–30 vs 37–49 age groups, the highest Sen rate was found as 0.75 with RF and ADA algorithms. The highest Sen rate of 25–30 vs 50–54 age groups was found as 0.85 with RF algorithm. In total sex comparison, the highest Sen rate was found as 0.81 with ADA algorithm (Table 7).

In the estimation of 25–30 vs 31–36 age groups, the highest F1 rate was found as 0.80 with RF algorithm. In the estimation of 25–30 vs 37–49 age groups, the highest F1 rate was found as 0.75 with RF and ADA algorithms. The highest F1 rate of 25–30 vs 50–54 age groups was found as 0.85 with RF algorithm. In total sex comparison, the highest F1 rate was found as 0.81 with ADA algorithm (Table 8).

The highest Acc rate was obtained with RF algorithm between 25–30 and 50–54 age groups and the

Table 4 Descriptive statistics of individuals between the ages of 50 and 54

Parameters	Sex	Median	Minimum	Maximum
Age (years)	Male	53.00	50.00	54.00
	Female	53.00	50.00	54.00
CT-L (cm)	Male	3.23	2.88	3.81
	Female	3.08	2.61	3.43
PNSCT-A (°)	Male	39.95	37.70	47.10
	Female	43.63	34.69	54.37
IFCT-A (°)	Male	159.35	128.51	179.80
	Female	157.79	113.13	177.38
FMRCT-L (cm)	Male	2.18	1.68	2.42
	Female	2.11	1.60	2.52
FMLCT-L (cm)	Male	2.25	1.67	2.61
	Female	2.18	1.60	2.48
PNSFM-A (°)	Male	88.22	76.65	105.78
	Female	99.95	79.92	143.29
IFFM-A (°)	Male	108.41	88.13	124.14
	Female	108.36	94.08	142.06
RFM-CL (cm)	Male	3.25	2.34	3.92
	Female	3.28	2.51	3.86
LFM-CL (cm)	Male	3.22	2.24	3.96
	Female	3.01	2.34	3.76
FM-L (cm)	Male	4.74	4.17	5.17
	Female	4.59	4.02	5.35
RFMTM-L (cm)	Male	1.81	1.11	2.30
	Female	1.85	1.29	2.31
LFMTM-L (cm)	Male	80.07	66.06	96.56
	Female	86.39	72.80	99.07
RM-A (°)	Male	82.07	67.19	95.76
	Female	79.09	66.62	106.23
LM-A (°)	Male	82.07	67.19	95.76
	Female	79.09	66.62	106.23

Table 5 Accuracy table of machine learning algorithms

Algorithms	25–30 vs 31–36	25–30 vs 37–49	25–30 vs 50–54	Total sex
DT	0.79	0.68	0.73	0.71
ETC	0.68	0.61	0.69	0.69
RF	**0.84**	**0.74**	**0.85**	0.77
LDA	0.68	0.65	0.81	0.69
QDA	0.79	0.58	0.69	0.67
LR	0.68	0.61	0.81	0.69
ADA	0.74	**0.74**	0.81	**0.81**

DT decision tree, ETC extra tree classifier, *RF* random forest, *LDA* linear discriminant analysis, *QDA* quadratic discriminant analysis, *LR* logistic regression, *ADA* AdaBoost classifier

Table 6 Specificity table of machine learning algorithms

Algorithms	25–30 vs 31–36	25–30 vs 37–49	25–30 vs 50–54	Total sex
DT	0.76	0.71	0.73	0.71
ETC	0.74	0.62	0.75	0.70
RF	**0.87**	**0.75**	**0.85**	0.78
LDA	0.60	0.68	0.82	0.69
QDA	0.79	0.58	0.70	0.70
LR	0.60	0.66	0.82	0.69
ADA	0.71	**0.75**	0.81	**0.81**

Table 7 Sensitivity table of machine learning algorithms

Algorithms	25–30 vs 31–36	25–30 vs 37–49	25–30 vs 50–54	Total sex
DT	0.79	0.71	0.73	0.71
ETC	0.68	0.62	0.69	0.69
RF	**0.84**	**0.75**	**0.85**	0.77
LDA	0.68	0.68	0.81	0.66
QDA	0.79	0.58	0.69	0.67
LR	0.68	0.66	0.81	0.69
ADA	0.74	**0.75**	0.81	**0.81**

Table 8 F1 table of machine learning algorithms

Algorithms	25–30 vs 31–36	25–30 vs 37–49	25–30 vs 50–54	Total sex
DT	0.76	0.64	0.73	0.71
ETC	0.71	0.62	0.68	0.69
RF	**0.80**	**0.75**	**0.85**	0.77
LDA	0.64	0.68	0.81	0.69
QDA	0.79	0.58	0.69	0.66
LR	0.64	0.61	0.80	0.69
ADA	0.72	**0.75**	0.81	**0.81**

confusion matrix of this algorithm is shown in Fig. 3. Thirteen of the 14 individuals in the test group between the ages of 25 and 30 were estimated correctly, while 1 was estimated incorrectly. Twelve of the 9 individuals in the test group between the ages of 50 and 54 were estimated correctly, while 3 were estimated incorrectly.

In our study, the SHAP analyzer belonging to the 25–30 vs 50–54 group with the highest accuracy rate with the RF algorithm was included and it was found that the PNSFM-A parameter contributed the highest to the overall result (Fig. 4).

In addition, tenfold cross-validation was applied to increase the reliability of our study, and the highest accuracy rate was found to be 84.55±2.06 in the 25–30 vs 50–54 group with the RF algorithm (Table 9).

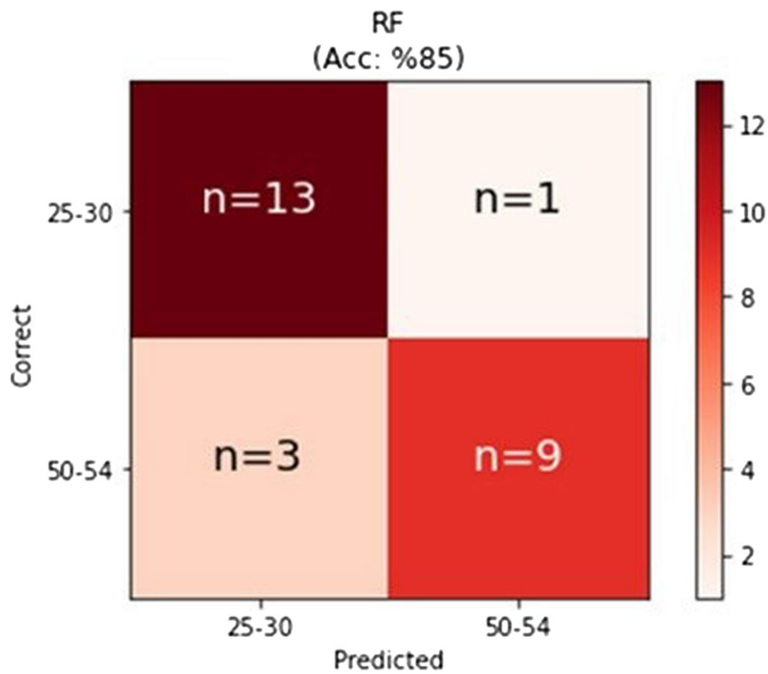

Fig. 3 Confusion matrix of the highest accuracy

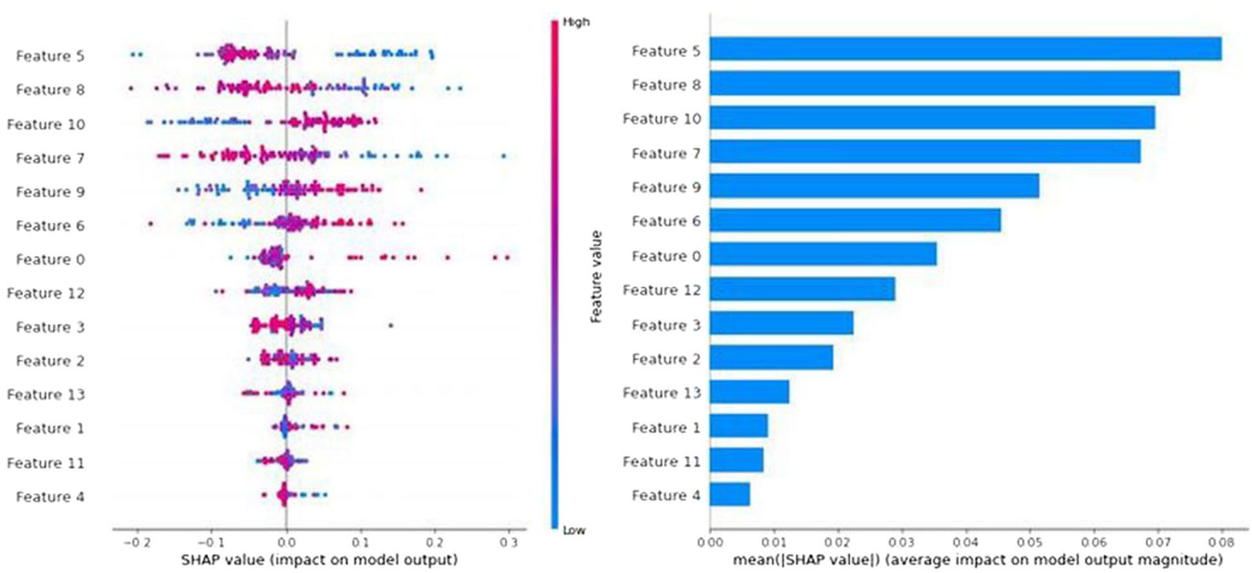

Fig. 4 SHAP analyzer of the RF algorithm (for group 25–30 vs 50–54, feature 0 CT-L, 1 PNSCT-A, 2 IFCT-A, 3 FMRCT-L, 4 FMLCT-L, 5 PNSFM-A, 6 IFFM-A, 7 RFM-CL, 8 LFM-CL, 9 FM-L, 10 RFMTM-L, 11 LFMTM-L, 12 RM-A, 13 LM-A)

Discussion

In the present study, sex and age estimation was performed by using ML algorithms with parameters of maxillary canine and molar teeth obtained from CBCT images. In sex estimation, an accuracy rate of 0.81 was obtained with ADA analysis, while in age estimation an accuracy of 0.85 was obtained between 25–30 and 50–54 groups with RF analysis.

Estimation of age from teeth is a research topic that started in 1837 and has survived to the present day. We can group methods of age estimation from teeth in three main categories; these are morphohistological, radiological, and biochemical methods. Of these methods,

Table 9 Tenfold cross-validation accuracy value

Groups	Algorithms	Mean ± standard deviation
25–30 vs 31–36	DT	76.67 ± 2.55
	ETC	66.54 ± 1.25
	RF	82.82 ± 1.92
	LDA	69.38 ± 1.49
	QDA	76.94 ± 1.63
	LR	69.06 ± 1.39
	ADA	71.25 ± 1.41
25–30 vs 37–49	DT	63.12 ± 2.10
	ETC	60.32 ± 1.22
	RF	67.95 ± 2.26
	LDA	62.24 ± 1.22
	QDA	58.14 ± 1.57
	LR	62.50 ± 1.39
	ADA	71.86 ± 2.71
23–30 vs 50–54	DT	66.74 ± 2.58
	ETC	68.32 ± 1.16
	RF	84.55 ± 2.06
	LDA	77.94 ± 1.14
	QDA	64.01 ± 2.15
	LR	79.56 ± 2.09
	ADA	78.08 ± 1.31
Cinsiyet	DT	64.51 ± 1.66
	ETC	66.34 ± 1.88
	RF	72.92 ± 1.66
	LDA	65.75 ± 1.36
	QDA	68.33 ± 1.57
	LR	66.29 ± 1.05
	ADA	78.66 ± 1.29

radiological methods have become more important both since they can be easily used in living and deceased individuals and also because of some laws that prohibit getting tissue from deceased individuals (Verma et al. 2019). When estimating age from teeth, radiological method CT comes to the fore because it provides thinner section and spatial resolution (Bjørk and Kvaal 2018). Different metric measurements of teeth have been used in radiological methods. Asif et al. (2019) evaluated the volumetric analysis of pulp/tooth ration by dividing individuals between 16 and 65 years of age into 5 different age groups and found that this volumetric analysis was valuable in age estimation. In a study, they used the pulp volume of the second molar in individuals between the ages of 21 and 50, Helmy et al. (2020) found that the second molar could be used in age estimation. In the present study, we determined 14 metric parameters from images of maxillary molar and canine teeth obtained with CBCT and obtained 0.85 Acc in age estimation with RF algorithm.

In a study they examined the maxillary and mandibular molar teeth of 1586 individuals by using convolutional neural network, Kim et al. (2021) divided individuals between 0 and 60 years of age into 7 different groups and obtained an accuracy rate between 0.89 and 0.90 in age estimation. In the present study, we performed age and sex estimation by using ML algorithms and found an accuracy rate of up to 0.85. When compared with Kim et al.'s study, we think that the reason for low Acc rate in our study is due to the high number of individuals in the study, and due to the fact that only molars were used and a different computer based algorithm was used.

In a study, they conducted on 100 female and 100 male individuals with parameters of the first molar, Sonika et al. (2011) found that the first molar showed sexual dimorphism. In a study they conducted on 100 women and 100 men, Manchanda et al. (2015) used seven maxillary and seven mandibular teeth and obtained sexual dimorphism between 0.51 and 0.80. Both studies in literature and our study show that maxillary molar and canine teeth show strong sexual dimorphism. In our study, 0.81 sexual dimorphism was found with ADA algorithm. The rates of other algorithms were found to vary between 0.69 and 0.77.

Limitations of the present study can be listed as scarcity of images, variety of algorithms used and the quality of CT used. However, despite these limitations, an Acc rate of 0.85 was obtained in age estimation, while an Acc rate of 0.81 was obtained in sex estimation.

Conclusions

As a result of our study, it was found that images of maxillary molar and canine teeth obtained from CBCT can be used as important biomarkers in sex and age estimation by using ML algorithms.

Abbreviations

CT	Computed tomography
ML	Machine learning algorithm
LR	Logistic regression
DT	Decision tree
RF	Random forest
LDA	Linear discriminant analysis
QDA	Quadratic discriminant analysis
ADA	AdaBoost classifier
ETC	Extra tree classifier
DICOM	Digital Imaging and Communications in Medicine
PACS	Picture Archiving Communication Systems
MPR	3D curved multiplanar reconstruction
Acc	Accuracy
Spe	Specificity
Sen	Sensitivity
F1	F1 score
FP	False positive
FN	False negative
TP	True positive
TN	True negative

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Availability of data and materials
The datasets generated and/or analyzed during the current study are not publicly available due [reason why data are not public] but are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Approval was obtained from the Inonu University Non-Interventional Ethics Committee with the decision no. 2020/1099.
Informed consent include appropriate statements.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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