A Study on Sex Estimation by Using Machine Learning Algorithms with Parameters Obtained from Computerized Tomography Images of the Cranium

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Abstract

The aim of this study is to test whether sex prediction can be made by using machine learning algorithms (ML) with parameters taken from computerized tomography (CT) images of cranium and mandible skeleton which are known to be dimorphic. CT images of the cranium skeletons of 150 men and 150 women were included in the study. 25 parameters determined were tested with different ML algorithms. Accuracy (Acc), Specificity (Spe), Sensitivity (Sen), F1 score (F1), Matthews correlation coefficient (Mcc) values were included as performance criteria and Minitab 17 package program was used in descriptive statistical analyses. $p \leq 0.05$ value was considered as statistically significant. In ML algorithms, the highest prediction was found with 0.90 Acc, 0.80 Mcc, 0.90 Spe, 0.90 Sen, 0.90 F1 values as a result of LR algorithms. As a result of confusion matrix, it was found that 27 of 30 males and 27 of 30 females were predicted correctly. Acc ratios of other MLs were found to be between 0.81 and 0.88. It has been concluded that the LR algorithm to be applied to the parameters obtained from CT images of the cranium skeleton will predict sex with high accuracy.

Introduction

The main purpose of forensic anthropology is to reconstruct the biological profile of deceased individuals; that is, to predict sex, age of death, lineage and height based on the remains of skeletons¹. Forensic sex prediction has taken a large place in literature since the late 1960s and identification of sex from human skeleton has been described as an important factor, even a key element in both forensic medicine and bio-archaeological context²⁻⁴. Sex prediction is an indispensable part of biological profile. Anthropologist uses the biomarkers of the skeletal system that vary between sexes to determine sex^{5,6}.

It is noteworthy that studies have been conducted in literature for the estimation of sex almost with all bones of the human skeleton and that the accuracy of gender determination has been researched frequently by comparing with different populations. It can be seen that various bones such as femur^{2,3}, patella^{7,8}, mandible⁹, calcaneus¹⁰, metatarsal bone and phalanx^{11,12}, occipital condyle¹³, hand bones^{14,15} and sternum¹⁶ are used in sex prediction. It has been reported in a large number of studies in literature that cranium and pelvis bones, which are considered to be the most dimorphic areas according to skeletal parts, can be used in sex prediction by using different assessment methods^{4,10,16-19}.

Identification of sex includes some inherent limitations that are affected by different factors such as ethnicity, socio-economic status, diet and geographic location. The inability to generalize the results obtained from a specific population, especially in skeletal parts such as cranium, to other populations and the need for population-specific studies increase the interest in cranium and mandible in sex determination^{4,20}. For these reasons, all techniques reported for identifying sex are specific to related studies and they may not be applicable to different samples or data sets³.

It can be seen that methods such as discriminant analysis, machine learning algorithms (ML), support vector machine and artificial neural network are commonly used in sex prediction in which these bones

are examined ^{2,3,7}.

ML is a modern classifier that is used extensively in the field of engineering, and it is now gradually integrated in the field of health. These algorithms are classified as supervised, unsupervised and reinforcement. Supervised learning is algorithms that match the relationship between input and output, unsupervised learning is algorithms that match the characteristics of the data about which there is no information and reinforcement learning is the algorithms that match the input data with desired characteristics ²⁰.

Computerized tomography (CT) is an imaging method that can show all tissues, especially bone tissue with sharp borders. In case of thin section, image orientation can be changed in three dimensions and can be taken to orthogonal plane. In this way, length and angle measurements can be calculated in a way that is less affected by orientation. With all these aspects, it provides superior results compared to studies carried out with more conventional osteometric devices ¹⁶.

The aim of this study is to show the success of sex prediction by using ML with parameters obtained from CT images of cranium and mandible skeleton.

Results

Of the 25 parameters determined, 20 (NVIC, NSVC, NNL, PC, NIVA, PNIC, VIC, NIC, RML, CML, GHGA, HML, COL, CMHA, HGGC, COIC, HGGMC, HGGMA) were found to be statistically significant between males and females ($p \leq 0.05$). In 18 of these parameters which were found to be statistically significant, the average of the parameter used was higher in males, while the average of the parameter used was higher in females in 2 parameters (GHGA, CMHA) (Table 1, 2).

Table 1
Comparison of parametric data of males and females

Parametre	Cinsiyet	Mean $\pm$ std (cm)	p value
NNL	Male	2.46 $\pm$ 0.34	< 0.01
	Female	2.30 $\pm$ 0.31	
NNZA	Male	120.68 $\pm$ 11.12	0.35
	Female	119.55 $\pm$ 9.92	
HGGA	Male	120.22 $\pm$ 6.90	0.92
	Female	120.30 $\pm$ 6.78	
RML	Male	5.29 $\pm$ 0.51	< 0.01
	Female	4.54 $\pm$ 0.41	
CML	Male	7.34 $\pm$ 0.57	< 0.01
	Female	7.06 $\pm$ 0.49	
GHGA	Male	37.05 $\pm$ 4.60	< 0.01
	Female	38.99 $\pm$ 4.87	
HML	Male	8.24 $\pm$ 0.56	< 0.01
	Female	7.55 $\pm$ 0.58	
COLI	Male	106.61 $\pm$ 6.98	0.06
	Female	105.07 $\pm$ 7.23	
CMHA	Male	110.68 $\pm$ 10.41	< 0.01
	Female	114.82 $\pm$ 10.04	
HGGC	Male	12.56 $\pm$ 0.79	< 0.01
	Female	11.44 $\pm$ 0.69	
COIC	Male	8.61 $\pm$ 0.73	< 0.01
	Female	7.93 $\pm$ 0.67	

(NNL: Nasion – nasal end point length, NNZA: Nasal end point – nasion – zygomatic angle, HGGA: Head of mandible– gonion – gnathion angle, RML: Ramus of the mandible length, CML: Corpus of the mandible length, GHGA: Gnathion – head of mandible– gonion angle, HML: Head of mandible – mental foramen length, COLI: Coronoid process – obliqua line – infradental angle, CMHA: Coronoid process – mandibular notch – head of mandible angle, HGGC: Head of mandible – gonion – gnathion curvature length, COIC: Coronoid process – obliqua line – infradental curvature length, HGGMA: Head of mandible – gonion – gnathion – mandibular notch area)

Parametre	Cinsiyet	Mean ± std (cm)	p value
HGGMA	Male	31.15 ± 4.10	< 0.01
	Female	25.57 ± 3.73	
(NNL: Nasion – nasal end point length, NNZA: Nasal end point – nasion – zygomatic angle, HGGA: Head of mandible– gonion – gnathion angle, RML: Ramus of the mandible length, CML: Corpus of the mandible length, GHGA: Gnathion – head of mandible– gonion angle, HML: Head of mandible – mental foramen length, COLI: Coronoid process – obliqua line – infradental angle, CMHA: Coronoid process – mandibular notch – head of mandible angle, HGGC: Head of mandible – gonion – gnathion curvature length, COIC: Coronoid process – obliqua line – infradental curvature length, HGGMA: Head of mandible – gonion – gnathion – mandibular notch area)			

Table 2
Comparison of non-parametric data of males and females

Parameter	Sex	Median (min-max), (cm)	p value
NVIA	Male	76.65 (69.54–86.03)	0.89
	Female	76.66 (43.77–86.43)	
NVIC	Male	32.41 (29.04–40.50)	< 0.01
	Female	30.84 (27.59–33.60)	
NSVC	Male	14.49 (12.20–18.14)	< 0.00
	Female	13.49 (11.43–38.97)	
ZA	Male	77.86 (62.76–95.62)	0.21
	Female	77.22 (43.65–92.02)	
PC	Male	4.67 (3.15–5.53)	< 0.01
	Female	4.14 (3.06–5.53)	
NIVA	Male	43.99 (14.18–73.93)	0.03
	Female	43.73 (37.23–51.16)	
PNIC	Male	39.47 (35.32–43.93)	< 0.01
	Female	37.13 (29.01–41.44)	
VIC	Male	17.78 (14.02–22.53)	< 0.0
	Female	17.28 (13.14–29.72)	
NFIA	Male	70.88 (45.18–81.06)	0.78
	Female	70.60 (60.79–80.64)	
NIC	Male	34.90 (31.12–38.12)	< 0.01
	Female	32.59 (23.45–37.39)	
GA	Male	125.31 (18.59–143.71)	0.18
	Female	125.58 (111.16–148.95)	
COL	Male	3.11 (2.13–7.36)	< 0.01
(NVIA: Nasion – vertex – inion angle, NVIC: Nasion – vertex – inion curvature length, NSVC: Nasion – superciliary arch – vertex curvature length, ZA: Zygomatic angle, PC: Piriform aperture curvature length, NIVA: Nasion – inion – vertex angle, PNIC: Piriform aperture – Nasal end point – inion curvature length, VIC: Vertex – inion curvature length, NFIA: Nasion – frontal tuber – inion angle, NIC: Nasal end point – inion curvature length, GA: Gonial angle, COL: Coronoid process – obliqua line length, HGGMC: Head of mandible – gonion – gnathion – mandibular notch curvature length)			

Parameter	Sex	Median (min-max), (cm)	p value
	Female	2.81 (1.94–3.85)	
HGGMC	Male	29.86 (17.62–33.83)	< 0.01
	Female	27.37 (23.08–32.79)	
(NVIA: Nasion – vertex – inion angle, NVIC: Nasion – vertex – inion curvature length, NSVC: Nasion – superciliary arch – vertex curvature length, ZA: Zygomatic angle, PC: Piriform aperture curvature length, NIVA: Nasion – inion – vertex angle, PNIC: Piriform aperture – Nasal end point – inion curvature length, VIC: Vertex – inion curvature length, NFIA: Nasion – frontal tuber – inion angle, NIC: Nasal end point – inion curvature length, GA: Gonial angle, COL: Coronoid process – obliqua line length, HGGMC: Head of mandible – gonion – gnathion –mandibular notch curvature length)			

0.90 Acc, 0.80 Mcc, 0.90 Spe, 0.90 Sen and 0.90 F1 values were found as a result of the LR algorithm. As a result of the confusion matrix performed, 27 of 30 males and 27 of 30 females were predicted correctly (Fig. 1). Of the MLs, the highest Acc, Mcc ratio was found as 0.90, 0.80 with LR algorithm. Acc ratios of the other MLs were between 0.81 and 0.88.

0.88 Acc, 0.77 Mcc, 0.88 Spe, 0.88 Sen, 0.88 F1 values were found as a result of LDA algorithm and 26 of 30 males and 27 of 30 females were predicted correctly as a result of confusion matrix. 0.83 Acc, 0.67 Mcc, 0.83 Sep, 0.83 Sen, 0.83 F1 values were found as a result of QDA algorithm and 24 of 30 males and 26 of 30 females were predicted correctly as a result of confusion matrix. 0.88 Acc, 0.77 Mcc, 0.88 Spe, 0.88 Sen, 0.88 F1 values were found as a result of RF algorithm and 24 of 30 males and 27 of 30 females were predicted correctly as a result of confusion matrix. 0.85 Acc, 0.70 Mcc, 0.85 Spe, 0.85 Sen, 0.85 F1 values were found as a result of ETC algorithm and 24 of 30 males and 27 of 30 females were predicted correctly as a result of confusion matrix. 0.81 Acc, 0.67 Mcc, 0.81 Spe, 0.81 Sen, 0.81 F1 values were found as a result of DT algorithm and 24 of 30 males and 23 of 30 females were predicted correctly as a result of confusion matrix.

Discussion

The aim of this study is to test whether sex identification can be made by using ML with the parameters obtained from cranium and mandible CT images taken to orthogonal plane. In the statistical analysis performed, NVIC, NSVC, NNL, PC, NIVA, PNIC, VIC, NIC, RML, CML, HML, COL, HGGC, COIC, HGGMC, HGGMA parameters were found to be statistically significant in distinguishing between sexes ($p \leq 0.05$). Of the MLs tested, 0.90 Acc, 0.80 Mcc, 0.90 Spe, 0.90 Sen, 0.90 F1 values were found as a result of LR algorithm. It was found that 27 of 30 males and 27 of 30 females were predicted correctly as a result of confusion matrix. Acc ratios of other MLs were found to be between 0.81 and 0.88. Forensic anthropologists constantly try to improve skeletal identification methods by using various methods in various parts of the skeleton or by developing new methods to determine gender⁴. Pelvis and cranium are known as the most dimorphic skeletal parts and they form the basis of sex determination researches^{4,10,17–19}. Bertsatos et al.¹⁹ reported that they predicted sex with an Acc ratio of 0.71–0.90 in total according to the results of the discriminant function analysis they carried out with the parameters taken

from the cranium. Franklin et al.²¹ and Dayal et al.²² reached Acc ratios of 0.88–0.90 and 0.80–0.85, respectively according to the results of the discriminant function analysis they carried out with the parameters taken from the cranium. In this study, 0.90 Acc, 0.80 Mcc, 0.90 Spe, 0.90 Sen, 0.90 F1 results were found as a result of LR algorithm. Since the ML results included Mcc value which can evaluate Acc, Spe, Sen values together and which shows the reliability of algorithm, it is thought that reliability and accuracy were tested with various methods and reliable results were found in the study¹².

While discriminant function analysis is one of the most widely used methods in forensic and archaeological cases for the determination of sex in literature, it is known that error rates are always different from 0%². The fact that the MLs used in the present study were trained as 80% training and 20% test set increases the prediction reliability of the study and makes it more advantageous when compared with discriminant analysis.

CT is preferred for providing advantage in the measurement of missing and damaged parts by making bone measurements very close to original and allowing for the reconstruction of each bone part, unlike conventional osteometry devices (calliper, odontometer, digital distance meter)^{16,23}. As far as we know, studies that associate parameters taken from cranium and mandible on orthogonal plane with ML based sex prediction are very limited. Even if CT is used in current studies, the results can show differences because the orientation of the image is not converted to the orthogonal plane since especially angular measurements are parameters affected by orientation.

In their study they predicted sex from cranium by using CT, Gillet et al.²⁴ used geometric morphometric model in their study and reported that they reached 0.90 Acc ratio for skull model. Zaafrane et al.²⁵ reported that they estimated sex with an Acc ratio of 0.90 from parameters of cranium in CT images they analysed by using basic statistical methods. These differences in results can be explained with the fact that the evaluation of sexually dimorphic features depend on group specific standards and skeletal characteristics differ among different populations, as well as the methodological methods used and differences in statistical analyses.

It has been reported in literature that the possibility of removing the mandible intact is high²⁶. The reason for this is the fact that the presence of a dense compact bone layer in the mandible makes it durable and therefore more likely to be found intact²⁷. It is reported in literature that the measurements taken from the mandible are generally obtained from panoramic radiography images and that these images are affected by orientation²⁸. According to the results of studies in which only the measurements taken from mandible are evaluated, an Acc ratio between 0.60 and 0.88 seems to be a reliable structure for sex prediction^{22,28–30}. In this study, combining the parameters taken from the mandible with the cranium strengthened gender prediction. RML, CML, GCGA, CFL, PLL, PICA, CGC, PLIC, CGGIC, CGGIA parameters taken from the mandible were found to be statistically significant in sex identification.

Since the identity of individuals should be predicted quickly and accurately in events such as war, natural disasters and fire, which deeply affect the society, the CT technology and MLs used in the present study

show that prediction time can be minimized and high accuracy can be obtained. Considering the high Acc ratio found as a result of LR algorithm, it is thought that the present study will strengthen and contribute to studies related with sex prediction.

Materials And Methods

Image Set and Population

The study was conducted at Karabuk University Training and Research Hospital, Department of Radiology after 2020/363 coded approval of Karabuk University Faculty of Medicine non-interventional clinical research ethics committee.

The image set in the study consisted of the CT images of 150 male and 150 female individuals whose ages ranged between 20 and 65. Individuals with any surgical operation or pathology of the cranium skeleton were excluded from the study. Average age of the males was 54 (min 20, max 65), while average age of the females was (min 21, max 65). No statistically significant difference was found between the average ages of males and females ($p = 0.395$).

Multidetector Ct (Mdct) Protocol

Radiological images used in the study were obtained from CT images with a section thickness of 5 mm taken in supine position by using a 16-row MDCT scanner (Aquilion 16; Toshiba Medical Systems, Otawara, Japan) in the department of radiology of a University Training and Research Hospital. Scanning protocol values were tube voltage: 120 kV, gantry rotation: 0,75 s and pitch: 1,0 mm.

Image Analysis

The images obtained were transferred to Horos Medical Image Viewer (Version 3.0, USA) program, which is a personal workstation in Digital Imaging and Communications in Medicine (DICOM) format. Images in sagittal, transversal and coronal planes were obtained from the transferred images by using 3D Curved Multiplanar Reconstruction (MPR). The line passing through the nasion and inion points of the images in these three planes was determined and all images were brought to the orthogonal plane (Fig. 2A). Later, CT images brought to orthogonal plane were overlapped by increasing their section thicknesses (Fig. 2B).

Length, angle, area and curvature length measurements of the anatomic points of the overlapped images were performed. These parameters and their abbreviations are listed below in Tables 3, 4 and 5. Demonstration of all evaluated parameters is shown in Fig. 3.

Table 3
Length parameters and abbreviations

Parameters	Abbreviations
Ramus of the mandible lenght	RML
Corpus of the mandible lenght	CML
Head of mandible – mental foramen length	HML
Coronoid process – obliqua line length	COL
Nasion – nasal end point lenght	NNL

Table 4
Angle parameters and abbreviations

Parameters	Abbreviations
Head of mandible– gonion – gnathion angle	HGGA
Gonial angle	GA
Gnathion – head of mandible– gonion angle	GHGA
Coronoid process – obliqua line – infradental angle	COLI
Coronoid process – mandibular notch – head of mandible angle	CMHA
Nasion – vertex – inion angle	NVIA
Zygomatic angle	ZA
Nasion – inion – vertex angle	NIVA
Nasal end point – nasion – zygomatic angle	NNZA
Nasion – frontal tuber – inion angle	NFIA

Table 5
Curve lenght- area parameters and abbreviations

Parameters	Abbreviations
Head of mandible – gonion – gnathion curvature length	HGGC
Coronoid process – obliqua line – infradental curvature length	COIC
Head of mandible – gonion – gnathion – mandibular notch curvature length	HGGMC
Nasion – vertex – inion curvature length	NVIC
Nasion – superciliary arch – vertex curvature length	NSVC
Piriform aperture curvature length	PC
Piriform aperture – Nasal end point – inion curvature length	PNIC
Vertex – inion curvature length	VIC
Nasal end point – inion curvature length	BIC
Head of mandible – gonion – gnathion – mandibular notch area	HGGMA

Machine Learning Algorithms

In this study, scikit-learn model (Version 0.20.0) in Python programming language (Version 3.7.1) was used to make ML modelling³¹. ML modelling was performed by using i7, 8 GbHp-Folio 1040 model computer. Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Extra Tree Classifier (ETC) algorithms were used. Algorithms were trained to be 80% training and 20% test set.

Performance Criteria

Accuracy (Acc), Specificity (Spe), Sensitivity (Sen), F1 score (F1), and Matthews correlation coefficient (Mcc) values were included as performance criteria.

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

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

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

$$Mcc = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$$

$$F1 = 2 \frac{\text{Specificity} \times \text{Sensitivity}}{\text{Specificity} + \text{Sensitivity}}$$

Equation 1. (TP: True positive, TN: True negative, FP: False positive, FN; False negative)

Statistical Analysis

Mean, standard deviation, minimum and maximum values were included in the descriptive statistics of each data according to gender groups. Normality test Anderson Darling test was applied to each parameter and it was checked whether the data were normally distributed. Two simple T test was applied to parametric data and Mann-Whitney U test was applied to nonparametric data and $p \leq 0.05$ value was considered as statistically significant. Minitab 17 package program was used in analyses.

Ethical considerations. This retrospective study was initiated with the 2020/363 decision of the Karabuk University Faculty of Medicine non-interventional clinical research ethics committee.

Declarations

Ethical approval.

The present study was approved by Karabuk University Faculty of Medicine Local Non-Interventional Clinical Trials Ethics Committee with the protocol number 2020/363. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent.

This study is retrospective and based on images taken from the hospital archive system. Therefore, the requirement for informed consent for the study was waived by the Karabuk University Faculty of Medicine Local Non-Interventional Clinical Trials Ethics Committee.

Contributions: S.T., Y.S. Z.O., M.K.T., S.O., and D.S. conceived and designed this research work. M.K.T., S.O., and Y.S. image collection and data analysis. All authors reviewed the manuscript.

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Conflict of Interest: The authors declare that there is no conflict of interest.

Footnote: This study was presented as an oral presentation at the 21st National Anatomy Congress in Turkey

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Figures

Figure 1

LR Confusion Matrix

Figure 2

A. Sagittal, transversal and coronal images brought to orthogonal plane, B. Overlapped image

Figure 3

Demonstration of parameters (1: NVIA, 2: ZA, 3: COIC, 4: HGGA, 5: VIC, 6: NNZA, 7: COLI, 8: CML, 9: NIC, 10: NIVA, 11: CMHA, 12: RML, 13: NNL, 14: COL, 15: GA, 16: NFIA, 17: HML, 18: HGGC, 19: NVIC, 20: PC, 21: GCGA, 22: PNIC, 23: HGGMA, 24: NSVC, 25: HGGMC)