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Gender estimation using machine learning algorithms from computed tomography images of clivus

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Abstract

The clivus, which is involved in the formation of the skull base, is an important material in gender prediction with its fusion structure. The aim of this study is to predict the gender of adult individuals using Machine Learning (ML) algorithms and Artificial Neural Networks (ANN) with parameters obtained from Computed Tomography (CT) images. The study was performed on CT images of 349 individuals aged 18-65 years. Clivus length, 1/3 upper, middle, and lower 1/3 width were measured on CT images and used in ML entry. As a result of the study, it was found that the clivus length, 1/3 upper, middle, and lower width had a significant difference in terms of gender, and ML algorithms showed accuracy up to 0.74. An accuracy of 0.67 was obtained with the ANN model. The study shows that clivus is a bone material that is open to research in terms of gender estimation and can be obtained with high accuracy. In this respect, we believe that it will guide the studies in forensic sciences.

Keywords: Clivus, computed tomography, machine learning algorithms, artificial neural networks, gender prediction

Introduction

The clivus is a part of the skull bone located at the base of the skull, between the foramen magnum and the dorsum sellae of the sphenoid bone, through which an important structure such as the spinal cord passes. Its ossification begins approximately at the age of 3 and ends at the age of 25. Since the clivus is a fused bone, it has a hard structure and is very resistant even to post-mortem burns [1-4].

Post-mortem identification is one of the most difficult topics in forensic science. Forensic science first tries to analyze four basic issues in identification. These are the ethnic origin, age at death, gender, and height of the deceased individual. Among these, gender has an important place and is even considered the basic step of identification [5].

Computed Tomography (CT) is an increasingly important radiologic imaging technique for forensic osteology. CT has important distinctive advantages such as allowing detailed three-dimensional examination, millimetre precision, high degree of sharpness, and cross-sectional examination [6]. In morphologic studies on dry bone and radiologic images, it has been reported that there is no difference between measurements made with conventional instruments such as calipers and radiologic measurement methods. This reveals the sensitivity of radiologic methods [6].

Machine learning (ML) algorithms can classify patterns that are very difficult for humans to distinguish by eye and can even identify new patterns that have not been identified before, which is why they are actively used in healthcare today [7]. Quadratic Discriminant Analysis (QDA) is a type of Linear Discriminant Analysis (LDA) that enables the classification of non-linear data [8]. Gaussian Naive Bayes (GaussianNB) is supervised machine learning and emerged from Bayes' theorem. It classifies the outputs by assuming that each parameter has the same effect

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on the result [9]. K-Nearest Neighbors (k-NN) algorithm is a common and simple algorithm that classifies inputs according to their "k" nearest neighbors and produces outputs [10]. Logistic regression (LR) is an old simple and widely used algorithm designed for binary outputs [11]. Decision Tree (DT) consists of two nodes, the leaf and the decision node, and is called the tree algorithm because its structure resembles a tree [12]. Random Forest (RF) is a classification algorithm that uses a large number of DT models to obtain outputs [13]. Extra Tree Classifier (ETC) is an ensemble algorithm and is very similar to the RF algorithm, the only difference is the structure of creating trees [14]. LDA is an ML algorithm that can classify linear data well, which is frequently preferred for gender prediction [15]. In summary, the most important differences of ML algorithms from traditional statistical methods are that they analyze the data in depth, reveal invisible differences, do not analyze only the mean or variance, separate the data into training and test sets and give more realistic and high sensitivity results. This is critical for accurate and in-depth identification of the biological profile in forensic studies [16].

Artificial neural networks (ANNs) have become prominent in forensic sciences due to their high gender prediction rate for non-linear data and the large number of learning techniques [17,18]. ANNs are based on the neuron model and consist of an input layer, hidden layer, and output layer [18,19].

The aim of this study is to predict gender using ML algorithms from the parameters of the clivus obtained using CT.

Material and Methods

The study was approved by the local ethics committee of Karabük University 08.11.2023 dated and 2023/1475 numbered. The study was performed on CT scans of 191 male and 158 female subjects aged 18-65 years. Individuals who had not undergone cranium surgery and did not have any pathology in the cranium were included in the study. Images were obtained randomly and retrospectively from individuals who met the inclusion criteria and had a CT scan between 2018 and 2023.

Images in Digital Imaging and Communications in Medicine (DICOM) format were transferred to Radiant Dicom Viewer (64 bit version). The transferred images were rendered in 3D using the 3D Volume Rendering console of the software. The lower 1/3 width of the clivus (the widest distance of the lower 1/3 of the clivus), the middle 1/3 width of the clivus (the widest distance of the middle 1/3 of the clivus), the upper 1/3 width of the clivus (the widest distance of the upper 1/3 of the clivus) and the length of the clivus (distance from the top to the bottom of the clivus midline) were measured on the 3D image. In addition, the accuracy of the measurements was confirmed by increasing and decreasing the slice thickness by using the 3D Multi-planar reconstruction (MPR) console of each image program for the clarity of the measurement limits. The measurements were performed by an expert radiologist with at least 5 years of experience (Figure 1).

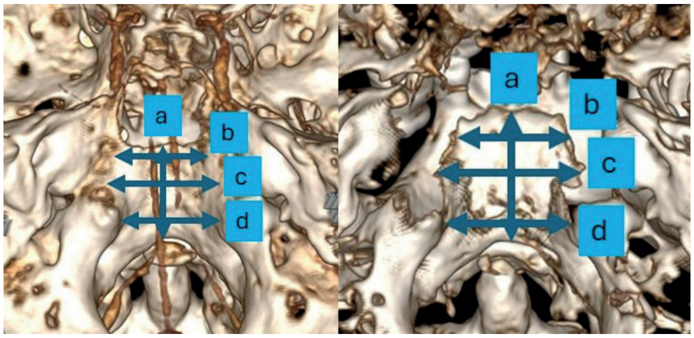

Figure 1. Measurement parameters of clivus

Machine Learning Algorithms and Application of Artificial Neural Networks

ML algorithms and ANN were analyzed using a Monster Abra model i5 computer. Python 3.9 was used to analyze the models. We selected 4 measurement parameters obtained from clivus as the input layer and gender as the output layer. 80% of the raw data was used as a training set. LDA, QDA, GaussianNB, k-NN, LR, DT, RF, ETC algorithms were preferred as ML models. The Multilayer Perceptron Classifier (MLCP) algorithm was preferred for artificial neural network applications. Accuracy (Acc), Specificity (Spe), Sensitivity (Sen), F1 score (F1) values were used to evaluate the performance of the models.

Statistical Analysis

Minitab 17 program was used for basic statistical analyses and $p<0.05$ was considered statistically significant. Anderson-Darling test was selected as normality test. Two sample T test and Mann Whitney U test were used to compare the data in terms of gender.

Results

As a result of the study, it was found that the parameters of the upper, middle and lower 1/3 width of the clivus were not normally distributed and these parameters were found to have a significant difference in terms of gender ($p<0.05$) (Table 1).

The clivus length parameter was also found to have a significant difference in terms of gender ($p<0.05$) (Table 2).

As a result of machine learning algorithms, it was found to be 0.74 with the GaussianNB algorithm (Table 3).

The GaussianNB algorithm correctly predicted 23 of 43 male and 20 of 27 female individuals in the test set (Figure 2).

We evaluated the contribution of the parameters for gender prediction with the SHAP solver of the RF algorithm and found that the parameter contributed the most (Figure 3).

As a result of the MLCP model of the ANN, performance values of 0.61 Acc, 0.61 Spe, 0.62 Sen, 0.61 F1 were obtained in 100 times training, 0.64 Acc, 0.63 Spe, 0.64 Sen, 0.63 F1 in 500 times training, and 0.67 Acc, 0.67 Spe, 0.68 Sen, 0.67 F1 in 1000 times training.

Table 1. Descriptive statistics for non-normally distributed data and gender comparisons

Parameters (mm)	Gender	Median (minimum-maximum)	p value*
Upper 1/3 width of the clivus	Male	30.00 (20.500-35.700)	.001
	Female	29.050 (25.800-33.500)	
Middle 1/3 width of the clivus	Male	22.800 (19.600-26.800)	.001
	Female	22.500 (19.400-25.200)	
Lower 1/3 width of the clivus	Male	21.200 (18.000-25.100)	.005
	Female	20.900 (17.700-23.500)	

*Mann Whitney U test

Table 2. Descriptive statistics of normally distributed data and comparison in terms of gender

Parameters (mm)	Gender	Mean±standard deviation	p value**
Clivus length parameter	Male	27.324±2.405	.001
	Female	26.092±2.319	

**Two Sample T test

Table 3. Performance results of machine learning algorithms

Algorithms	Acc	Spe	Sen	F1
GaussianNB	74	75	76	74
RF	61	59	58	58
ETC	60	59	59	59
QDA	66	65	65	65
LDA	63	61	61	61
DT	69	67	68	67
LR	67	65	66	66
k-NN (k=15)	69	69	70	68

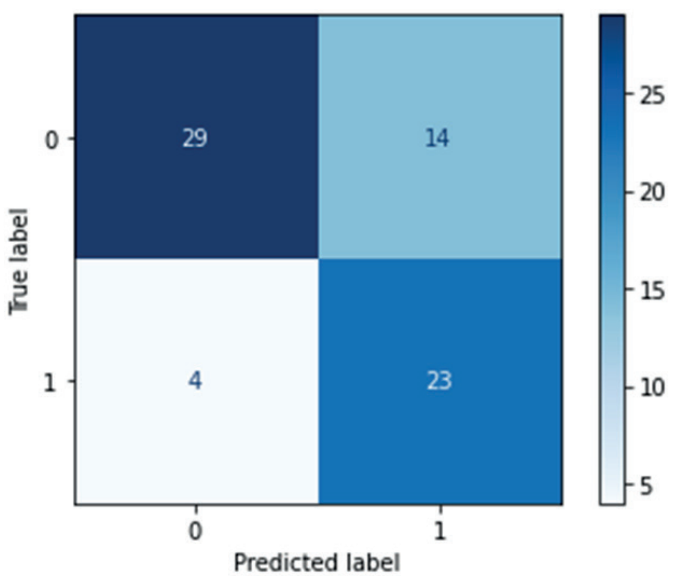

Figure 2. Confusion matrix table of the algorithms with the highest performance

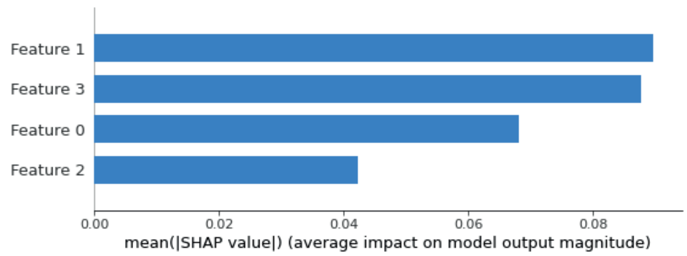

Figure 3. SHAP decoder of the RF algorithm (Feature 0: Upper 1/3 width of Clivus, 1: Middle 1/3 width of Clivus, 2: Lower 1/3 width of Clivus, 3: Clivus length)

Discussion

In this study, an accuracy rate between 0.60-0.74 was obtained by using ML algorithms with the parameters of the clivus obtained from CT images. The highest contribution to this accuracy rate was found to be provided by the middle 1/3 width of the clivus. In addition, ANN was used in the study and an accuracy of 67% was achieved.

Defining the biological profile is important in forensic studies and the first biological characteristic to look at is sex. The accuracy of sex varies depending on the measurement material taken as a basis, the state of preservation of the measurement material in nature, the population in which the measurement material is found, and the correct technique [20].

There are three metadologies in forensic science for sex estimation. These are molecular, morphological and metric methods. Among these, metric methods stand out as being shorter and less costly than molecular methods and more sensitive and closed to observational changes than morphological methods [21-24].

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ML algorithms based on artificial intelligence are preferred in current studies in gender prediction. According to the literature, ML algorithms increase the accuracy rate in gender prediction and produce more objective results [25]. Gender prediction studies were conducted on different bones using ML algorithms. For example, accuracy rates of 0.88 with tarsal bones, 0.92 with pelvis, 0.96 with cranium, and up to 0.92 with long bones were obtained [7,16,26,27]. To the best of our knowledge, there is no gender prediction study in the literature using ML algorithms with parameters obtained directly from clivus.

The margin of error of CT measurements compared to real bone was a matter of curiosity for many years [28]. Franklin et al. used both dry bone and CT images for skull measurements and reported that the results were consistent with both techniques and the margin of error was negligible [29]. Cone beam CT (CBCT) is a more flexible imaging modality than closed CT imaging. Because the image is obtained by rotating the device around the patient [30]. CBCT is more preferred in forensic dentistry studies due to the curved structure of the maxilla and mandible bones [31]. In this study, CT imaging was preferred because the skull bone was preferred.

Shalini et al. reported that clivus length and clivus width parameters had a significant difference in terms of gender in their study on CBCT images of 162 male and 92 female individuals aged 6-70 years [1]. In Chaurasia et al.'s study on CBCT images of 130 male and 70 female individuals between the ages of 6-78 years, they found that the clivus length was longer in males and had a significant difference according to gender [32]. Sharma et al. In their study on CT images of 142 male and 136 female individuals aged 11-69 years, they found the clivus length to be 4.608±0.315 cm in males and 4.391±0.247 cm in females and correctly classified 67.61% of male and 77.94% of female individuals by analysis of variance [33]. Abdolmaleki et al. found the length of the clivus to be 45.72 mm in men and 41.56 mm in women in their study on CBCT images of 130 male and 130 female adults and reported that there was a significant difference in terms of gender [34]. Özalp et al. 24 found the length of the clivus to be 24.83±3.91, the width of the upper 1/3 of the clivus to be 20.27±3.07, the width of the middle 1/3 of the clivus to be 21.77±2.75, and the width of the lower 1/3 of the clivus to be 28.83±3.72 using CT in their study on dry skulls [35]. In our study, we used CT images of 191 male and 158 female adults and found that clivus length and clivus upper/middle/lower 1/3 width parameters were significantly different according to gender. In addition, an accuracy rate of up to 74% was obtained with the ML study.

Conclusion

The limitations of the study include the small population and the lack of different techniques. As a result of the study, it was concluded that clivus can be used in gender estimation. We believe that further studies with clivus will contribute to forensic sciences.

The study was presented as an oral presentation at the 15th International Medicine and Health Sciences Researches Congress (23-24 March 2024, Ankara).

Conflict of Interests
The authors declare that there is no conflict of interest in the study.

Financial Disclosure
The authors declare that they have received no financial support for the study.

Ethical Approval
The study was approved by the local ethics committee of Karabük University 08.11.2023 dated and 2023/1475 numbered.

References

1. Shalini K, Katne T, Gotoor S, et al. Radiomorphometric analysis of the clivus–A soothsayer of age and gender. Journal of Oral and Maxillofacial Radiology. 2022;10:69-75.

2. Tangrodchanapong T, Yurasakpong L, Suwannakhan A, et al. Basilar tubercles and eminences of the clivus: Novel anatomical entities. Ann Anat. 2023;250:152133.

3. Krmpotić-Nemanić J, Vinter I, Kelovizć Z, Marušić A. Postnatal changes of the clivus. Ann Anat. 2005;187:277-80.

4. Samii M, Knosp E. Approaches to the clivus: approaches to no man's land: Springer Science & Business Media. 1st edition. Springer-Verlag, Hannover, 2012;1-128.

5. Zhan MJ, Cui JH, Zhang K, et al. Estimation of stature and sex from skull measurements by multidetector computed tomography in Chinese. Leg Med (Tokyo). 2019;41:101625.

6. Isaza J, Díaz CA, Bedoya JF, et al. Assessment of sex from endocranial cavity using volume-rendered CT scans in a sample from Medellín, Colombia. Forensic Sci Int. 2014;234:186.e1-10.

7. Toneva D, Nikolova S, Agre G, et al. Machine learning approaches for sex estimation using cranial measurements. Int J Legal Med. 2021;135:951-66.

8. Ha DH, Nguyen PT, Costache R, et al. Quadratic discriminant analysis based ensemble machine learning models for groundwater potential modeling and mapping. Water Resources Management. 2021;35:4415-33.

9. Naiem S, Khedr AE, Marie M, Idrees AM. Enhancing the efficiency of gaussian naïve bayes machine learning classifier in the detection of DDOS in cloud computing. IEEE Access. 2023;PP:1-1.

10. Laaksonen J, Oja E. Classification with learning k-nearest neighbors. Proceedings of international conference on neural networks (ICNN'96); 1996;3:1480-3.

11. Musa AB. Comparative study on classification performance between support vector machine and logistic regression. Int J Mach Learn & Cyber. 2013;4:13-24.

12. Bansal M, Goyal A, Choudhary A. A comparative analysis of K-nearest neighbor, genetic, support vector machine, decision tree, and long short term memory algorithms in machine learning. Decision Analytics Journal. 2022;3:100071.

13. Rodriguez-Galiano V, Sanchez-Castillo M, Chica-Olmo M, Chica-Rivas M. Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. Ore Geology Reviews. 2015;71:804-18.

DOI: 10.5455/medscience.2024.05.046

14. Kumar P, Singh SN, Dawra S. Software component reusability prediction using extra tree classifier and enhanced Harris hawks optimization algorithm. Int J Syst Assur Eng Manag. 2022;13:892-903.

15. Santos F, Guyomarc'h P, Bruzek J. Statistical sex determination from craniometrics: Comparison of linear discriminant analysis, logistic regression, and support vector machines. Forensic Sci Int. 2014;245:204.e1-8.

16. Navega D, Vicente R, Vieira DN, et al. Sex estimation from the tarsal bones in a Portuguese sample: a machine learning approach. Int J Legal Med. 2015;129:651-9.

17. Kartal E, Etli Y, Asirdizer M, et al. Sex estimation using foramen magnum measurements, discriminant analyses and artificial neural networks on an eastern Turkish population sample. Leg Med (Tokyo). 2022;59:102143.

18. Patil V, Vineetha R, Vatsa S, et al. Artificial neural network for gender determination using mandibular morphometric parameters: a comparative retrospective study. Cogent Engineering. 2020;7:1723783.

19. Xie X, Wang L, Wang A. Artificial neural network modeling for deciding if extractions are necessary prior to orthodontic treatment. Angle Orthod. 2010;80:262-6.

20. Krishan K, Chatterjee PM, Kanchan T, et al. A review of sex estimation techniques during examination of skeletal remains in forensic anthropology casework. Forensic Sci Int. 2016;261:165.e1-8.

21. Brůžek J, Santos F, Dutailly B, et al. Validation and reliability of the sex estimation of the human os coxae using freely available DSP2 software for bioarchaeology and forensic anthropology. Am J Phys Anthropol. 2017;164:440-9.

22. Babu YR, Kanchan T, Attiku Y, et al. Sex estimation from foramen magnum dimensions in an Indian population. J Forensic Leg Med. 2012;19:162-7.

23. Tunis TS, Sarig R, Cohen H, et al. Sex estimation using computed tomography of the mandible. Int J Legal Med. 2017;131:1691-700.

24. Gupta R, Nayyar AK, Gupta MK, Bhagat OL. Forensic tool for sex prediction-hand dimensions. Afr Health Sci. 2022;4:408-12.

25. Ortiz AG, Costa C, Silva RHAd, et al. Sex estimation: Anatomical references on panoramic radiographs using Machine Learning. Forensic Imaging. 2020;20:200356.

26. Coelho JdO, Curate F. CADOES: an interactive machine-learning approach for sex estimation with the pelvis. Forensic Sci Int. 2019;302:109873.

27. Knecht S, Santos F, Ardagna Y, et al. Sex estimation from long bones: a machine learning approach. Int J Legal Med. 2023;137:1887-95.

28. Battan SK, Sharma M, Gakhar G, et al. Cranio-facial bones evaluation based on clinical CT data for sex determination in Northwest Indian population. Leg Med. 2023;64:102292.

29. Franklin D, Cardini A, Flavel A, et al. Concordance of traditional osteometric and volume-rendered MSCT interlandmark cranial measurements. Int J Legal Med. 2013;127:505-20.

30. Fontana F, Piacentino F, Ierardi AM, et al. Comparison between CBCT and fusion PET/CT-CBCT guidance for lung biopsies. Cardiovasc Intervent Radiol. 2021;44:73-9.

31. Gamba Tde O, Alves MC, Haiter-Neto F. Mandibular sexual dimorphism analysis in CBCT scans. J Forensic Leg Med. 2016;38:106-10.

32. Chaurasia A, Katheriya G, Patil R. Radiomorphometric evaluation of Clivus in Indian ethinicity-A cone beam computed tomography study. J Oral Med Oral Surg Oral Pathol Oral Radiol. 2017;3:35-41.

33. Sharma SK, Jehan M, Gupta R, Trivedi A. Determination of gender & age by clival length using CT scan. International Journal of Medical Toxicology & Legal Medicine. 2014;16:65-70.

34. Abdolmaleki M, Ghafari R, Pourkhalili R. Analysis of morphological and anthropometric variations of clivus using cone beam computed tomography in adults. Caspian J Dent Res. 2021;10:19-26.

35. Özalp H, Beğer O, Erdoğan O, et al. Morphometric analysis of the clivus in human dry skulls: a radioanatomical study. J Ankara Univ Fac Med. 2019;72:227-30.