# Sex classification accuracy through machine learning algorithms - morphometric variables of human ear and nose

Tej Kaur[1], Kewal Krishan[2]*, Akanksha Sharma[1], Ankita Guleria[2] and Vishal Sharma[1]

## Abstract

**Objective**  Sex determination is an important parameter for personal identification in forensic and medico-legal examinations. The study aims at predicting sex accuracy from different parameters of ear and nose by using a novel approach of Machine Learning Library, 'PyCaret'.

**Results**  The present research was carried out on 508 participants (264 males and 244 females) aged 18–35 years from north India. Various ear and nose measurements were recorded on each participant. PyCaret employs a train-eval-testing validation approach, yielding a comprehensive output of the model in the form of a table that consolidates the average scores of all models over ten folds, including the respective time values. These models were compared based on performance metrics, and time taken. The logistic regression classifier emerged as the top-performing model, achieving the highest scores of 86.75% for sex prediction accuracy. Nasal breadth has been concluded as the most significant variable in accurate sex prediction. The findings indicate that the majority of the ear and nose characteristics significantly contribute to sexual dimorphism. This novel approach for sex classification can be efficiently used in a variety of forensic examinations and crime scene investigation especially where there is a need for estimation of sex for personal identification.

**Keywords**  Human anatomy and morphology, Ear and nose morphology, Forensic identification, Machine learning algorithms, PyCaret, Sex classification

## Introduction

Sexual dimorphism is a pervasive phenomenon among all species [1]. Determination of sex is population explicit, which is well proven for many populations [2]. According to the definition by Britannica [3], sexual dimorphism is the systematic difference in form between individuals of different sex in the same species. In general, dimorphism in males and females unveils in size, physique, body shapes, voices, hair, face, beard/moustache, breasts, etc. which could be easily seen and identified [4].

In forensic investigations, the sex identification can reduce the search and the consequently the burden of the investigating agency by half [5–7]. Human face plays a considerable role in sexual dimorphism. The suspects and offenders can be identified on the basis of certain facial traits [8]. Moreover, personal identification greatly depends upon facial characteristics in living individuals [9]. Human face may represent the ancestry, ethnicity, age and sex of an individual. Amongst all facial features,

*Correspondence:
Kewal Krishan
gargkk@yahoo.com
[1]Institute of Forensic Science and Criminology, Panjab University, Sector-14, Chandigarh, India
[2]Department of Anthropology, (UGC Centre of Advanced Study), Panjab University, Sector-14, Chandigarh, India

ear and nose can be potentially used as a tool for identification and individualization of a person. There are instances when both ear and nose are visible through CCTV cameras wherein other part of the face is covered [10, 11]. Human nose is one of the most distinguishing facial features for individual identification. According to Guleria et al. [12]., genetic and environmental factors affect the shape, size and morphology of nose. Various morphological and metric traits of nose vary between males and females making nose a useful indicator for sex estimation in forensic anthropology. Sarilita et al. [13] observed statistically significant larger nasal dimensions in males than females. Similarly, human ear is also distinct for every individual making it a unique biometric trait and also an indicator for sex estimation. Sezgin and Ersoy [14] found sex-differences in the helix and earlobe forms. These two features of the face are still newer and have little recognition to the level of fingerprints and iris as proof of distinctiveness. The role of external ear as an identification marker has been dated back to the time of Bertillon who mentioned in his book that it is impossible for both ears to be identical in all their parts [15]. According to the research done by Iannarelli on the stages of ear development, proportions of ear do not change after fourth month of intra uterine life, however its size continue to increase [16].

On the other hand, nose is the most protuberant, visible and centrally placed part of the human face that is pyramidal in shape [17]. External nose can be potentially used as a tool for identification and individualization of a person [18]. The structural frame of the nose has a strong impact on complete facial aesthetics [19, 20]. Its placement and outline provide congruence and poise to the face, making it an important organ for plastic surgeons to conduct cosmetic surgeries i.e. rhinoplasty [21].

Understanding the morphometry of the human ear and nose has several practical applications. It is relevant in fields such as plastic surgery, where knowledge of nasal proportions and variations assists in surgical planning and achieving desired aesthetic outcomes [22]. Additionally, nose anthropometry contributes to facial reconstruction efforts in forensic science and aids in the design of facial masks and respirators for proper fit and functionality [23, 24]. Therefore, the present investigation is attempting at devising models for sex determination and predicting sex accuracy from different parameters of ear and nose by using a novel approach of Machine Learning Library, 'PyCaret'.

## Materials and methods
### Study participants and the area
The present study was conducted on 508 participants (264 males and 244 females) within the age group of 18–35 years from a north Indian population. Participants with a previous history of craniofacial trauma, ear and nose diseases, cleft lip, congenital anomalies or who have undergone facial surgery were not included in the sample.

### Standardization for anthropometric measurements of nose and ear
The measurements were taken with the help of sliding caliper on the ear (left and right) and nose of each participant. The measurements were standardized according to the techniques described by Hall et al. [25] and Singh and Bhasin [26]. The anthropometric landmarks were marked with the help of skin marking pencil on the ear and nose. Then with the help of standardized instruments, the measurements were taken.

The snapshots of the subject's ear (both right and left) and nose (frontal, basal and lateral) were taken with the help of Sony Cybershot DSCW80 7.2MP Digital Camera placed on a tripod stand and the face of the subject was held in Frankfurt Horizontal plane. In case of nose, for the lateral and frontal view, pictures were clicked from the distance of 35 cm between the subject and the camera mounted on the camera stand. For the basal view, the camera was adjusted accordingly at an approximate distance of 12 cm. In case of ear, the distance was nearly 30 cm.

The precision estimates of measurements were calculated by taking repeated measurements on thirty participants. Each measurement was taken twice by the same investigator on the same participant. The technical error of measurement (TEM), relative technical error of measurement (rTEM), and the coefficient of reliability (R) were calculated to obtain intra-observer precision [27, 28].

### Anthropometric variables of ear and nose
Total number of measurements taken from ear were ten (from both left and right) and that from nose were five; totaling the count to twenty-five. The measurements of ear (A-J) and nose (K-O) along with the definition and references are shown in Supplementary Table S1. The pictorial representation of ear and nose measurements is depicted in Figs. 1 and 2, respectively.

### Data modeling in Python
The data modelling procedure employed the low-code open-source machine learning library PyCaret, known for its adaptability across various Machine Learning (ML) algorithms to handle binary and multi-class classification problems [30]. In this study, 15 classifiers in PyCaret python library were compared and underwent evaluation, and their details are delineated in Supplementary Table S2, complete with references. PyCaret employs a train-eval-testing validation approach, yielding a
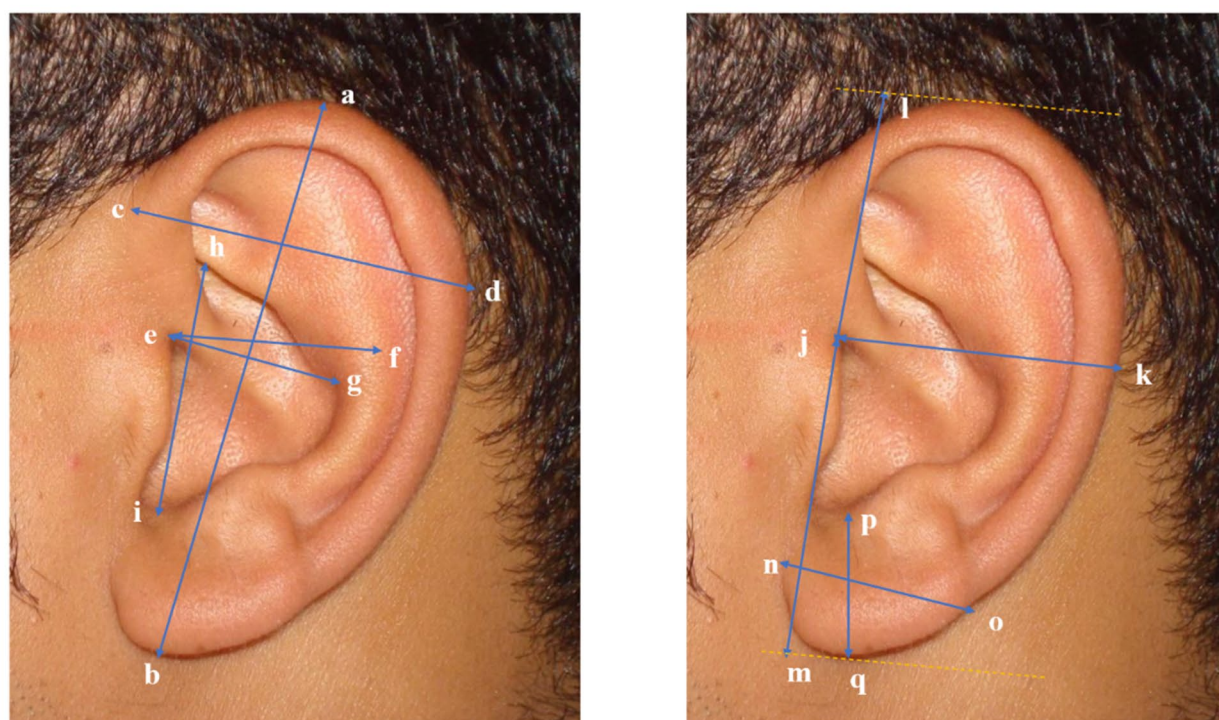
**Fig. 1** Anthropometric measurements of human ear (left): **a-b** Physiognomic ear length; **c-d** Physiognomic ear breadth; **e-f** Tragus antihelix distance; **e-g** Conchal width; **h-i** Conchal length; **j-k** Tragus helix distance; **j-l** Ear length above tragus; **j-n** Ear length below tragus; **n-o** Lobular width; **p-q** Lobular length
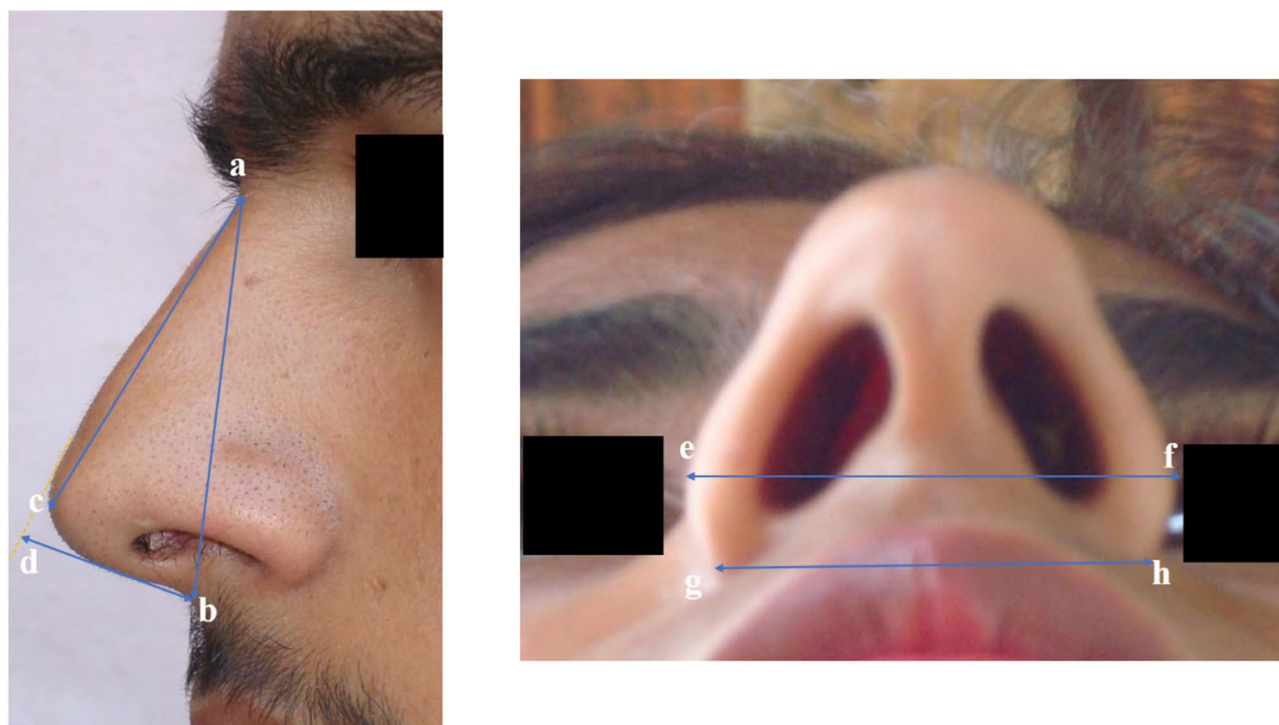


**Fig. 2** Lateral (**A**) and Inferior (**B**) view of anthropometric measurements of Nose: **a-b** Nasal height; **a-c** Total length of nasal bridge; **b-d** Nasal depth; **e-f** Nasal breadth; **g-h** Anatomical width of nose

comprehensive output of the model in the form of a table that consolidates the average scores of all models over ten folds (by default), including the respective time values. The classification metrics in the output encompass accuracy, area under the curve (AUC), recall, precision, F1, Cohen's kappa, the Matthews correlation coefficient (MCC), and the time taken (TT) by the classifier. Accuracy gauges the proportion of accurate predictions made by the trained model; AUC evaluates binary classifier performance. Recall measures correctly identified positive instances, while precision accesses accurately predicted positives. Additionally, F1-score is the harmonic mean of precision and recall and expresses efficacy of the model. In addition to evaluating individual classification algorithms, Cohen's kappa evaluates effectiveness of the classification algorithms as a whole. MCC balances true positive and false positive rates, and TT signifies algorithm fitting and prediction time. These metrics are presented as percentages. Additionally, PyCaret streamlines pre-processing tasks, including standardization, handling imbalanced data, hyperparameter tuning, and potential feature engineering. Since there were only twenty-five features which had been investigated, feature selection was excluded.

## Results

The results of the three most commonly used precision estimates were calculated i.e., technical error of measurement (TEM), the relative technical error of measurement (rTEM) and coefficient of reliability (R) are presented in Supplementary Table S3. The TEM values were ranged between 0.09 and 0.17 (in cm). The rTEM values were within 1.79–10.25%. The reliability for the intra-observer error ranged between 0.38 and 0.97 cm. The concha length of right ear was the only measurement was observed with poor reliability ($R = 0.38$), while ear length above tragus ($R = 0.62$), conchal length of left ear ($R = 0.65$), tragus to antihelix distance of right ear ($R = 0.64$), tragus to helix distance ($R = 0.68$), ear lobule width of right ear ($R = 0.57$) and conchal width of right ear ($R = 0.69$) were observed with moderate reliability. Whereas rest of the measurements were close to 1, observed with good reliability which is considered within an acceptable range [27–29].

### Data modeling

The dataset consists of 26 columns (ear & nose variables) and 508 rows (participants under study), where each row represents an individual sample. All columns contain complete data, amounting to 508 non-null values, and their data types are specified, predominantly as float64 (floating point numbers data type), except for the "SEX" column, categorized as an object. In this study, a dataset comprising 508 entries and 26 columns

is employed, detailed in the Supplementary Table S4. The variables likely relate to ear and nose, commonly employed for predicting age, sex, plastic surgeries, facial reconstruction and associated medical conditions. Standard nose measurement variables encompass "NASAL HEIGHT", "NASAL BREADTH", "NASAL DEPTH", "TOTAL LENGTH OF NASAL BRIDGE", and "ANATOMICAL WIDTH OF NOSE". Conversely, variables like "PEL", "PEB", "ELAT", "ELBT", "TAD", "THD", "ELH", "ELW", "CL", and "CW" represent left and right ear measurements. The target variable "SEX" indicates whether samples belong to the 'male' or 'female' category.

The evaluation of data distribution entails calculating key summary statistics, including mean, median, mode, and standard deviation for each variable. It is essential to visually grasp the shape of the distribution, which can be accomplished through distribution (histograms and density) plots (Fig. 3). Understanding data distribution is crucial as it can impact the effectiveness of machine learning algorithms, subsequently influencing prediction accuracy. In this study, 26 parameters are utilized, with sex (male or female) as the target feature. The determination of sex incorporates the other 25 parameters as input variables in the calculation process. This comprehensive analysis of data distribution plays a pivotal role in optimizing machine learning outcomes and improving prediction precision.

### Sex classification experiment

The included dataset exhibits an uneven distribution of samples across both categories, with 264 male and 244 female samples. To ensure unbiased binary classification through machine learning algorithms in PyCaret, class balancing becomes imperative. SMOTE (Synthetic Minority Over-sampling Technique) was employed to rectify this imbalance, artificially augmenting the sample count of female category. Additionally, data preprocessing included normalizing the dataset through the z-score method. The complete dataset underwent random splitting, allocating 30% of instances for "test" to evaluate classification and generalization performance, and the remaining 70% for training, employing stratified K-fold cross-validation across ten repetitions. Subsequently, 368 instances were used for training, with the remaining 153 for model validation (test data). The comparison of various models based on performance metrics, including accuracy, recall, precision, F1-score, kappa, MCC, and time taken, is presented in Supplementary Table S5. The logistic regression (LR) classifier emerged as the top-performing model, achieving the highest scores of 86.75% for accuracy and recall (approximately 0.3% higher than LDA), 94.15% for AUC (about 1% higher than LDA), 87.18% for precision (approximately 1% higher than LDA), 86.7% for F1-score (around 0.3%
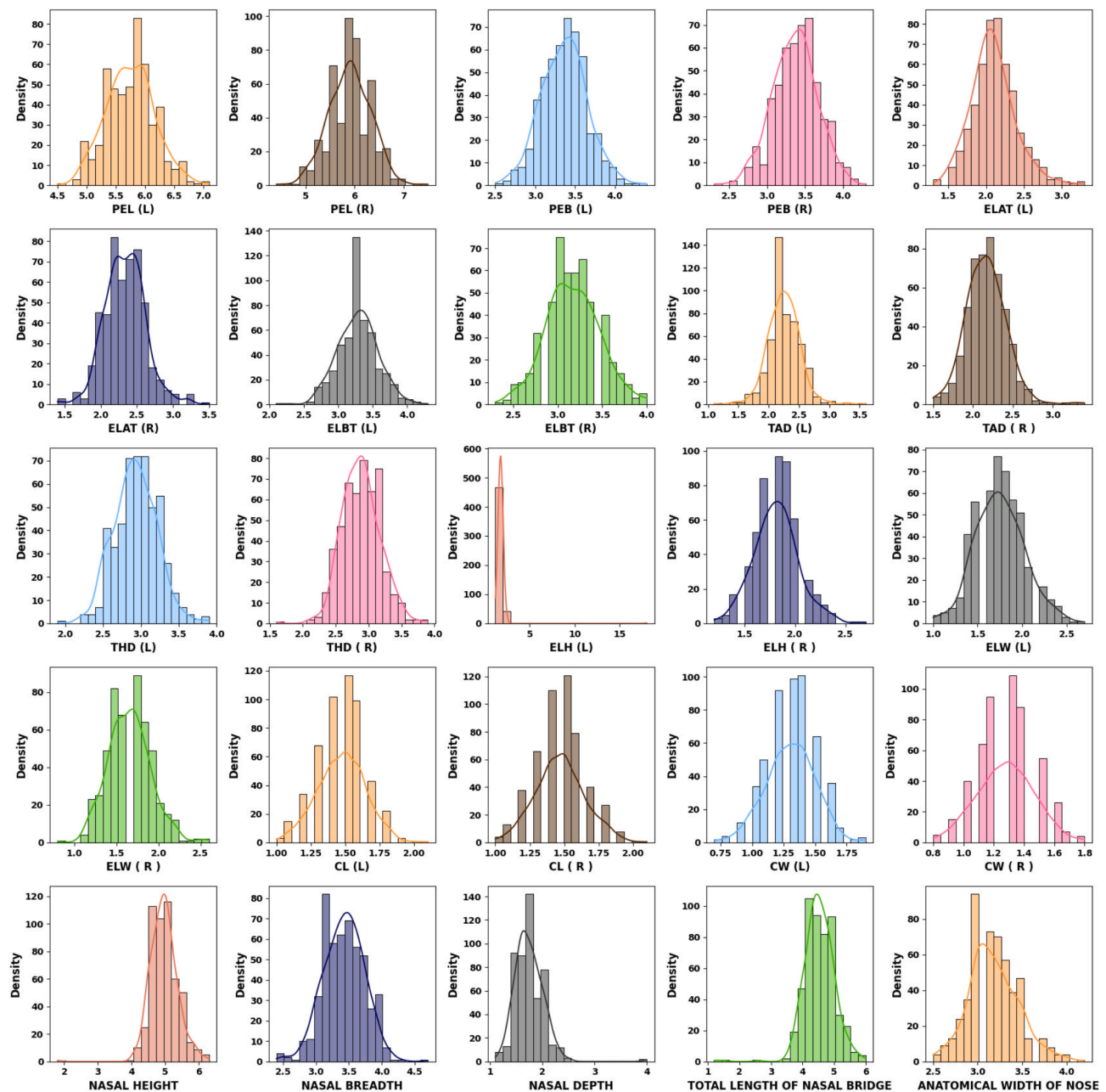
**Fig. 3** Density plots for different features used in the dataset

higher than LDA), 73.46% for Kappa (approximately 1% higher than LDA), and 73.89% for MCC (approximately 0.7% higher than LDA), all achieved in a mere 0.0930 s. In contrast, the dummy classifier exhibited the poorest performance, with an accuracy and recall of 48.17%, an AUC of 0.5, precision of 23.22%, F1-score of 31.33%, and zero values for kappa and MCC metrics. The LR classifier, identified as the best performer, underwent further hyper-tuning, resulting in enhanced accuracy, recall, precision, F1-score, Kappa, and MCC metrics, as detailed in Supplementary Table S6.

The performance measurement for the LR classifier at various thresholds was assessed using the ROC (Receivers Operating Characteristics) curve and AUC (Area Under the Curve) value to determine the discriminating capabilities of the model between classes. The ROC curve for LR classifier (Fig. 4a) plots the false positive rate on the x-axis and true positive rate on the y-axis, revealing an AUC value of 0.88 for the classes (0 for male and 1 for female), with identical micro- and macro-average values for the ROC curve. This outcome indicates the strong ability of the trained model to distinguish between male
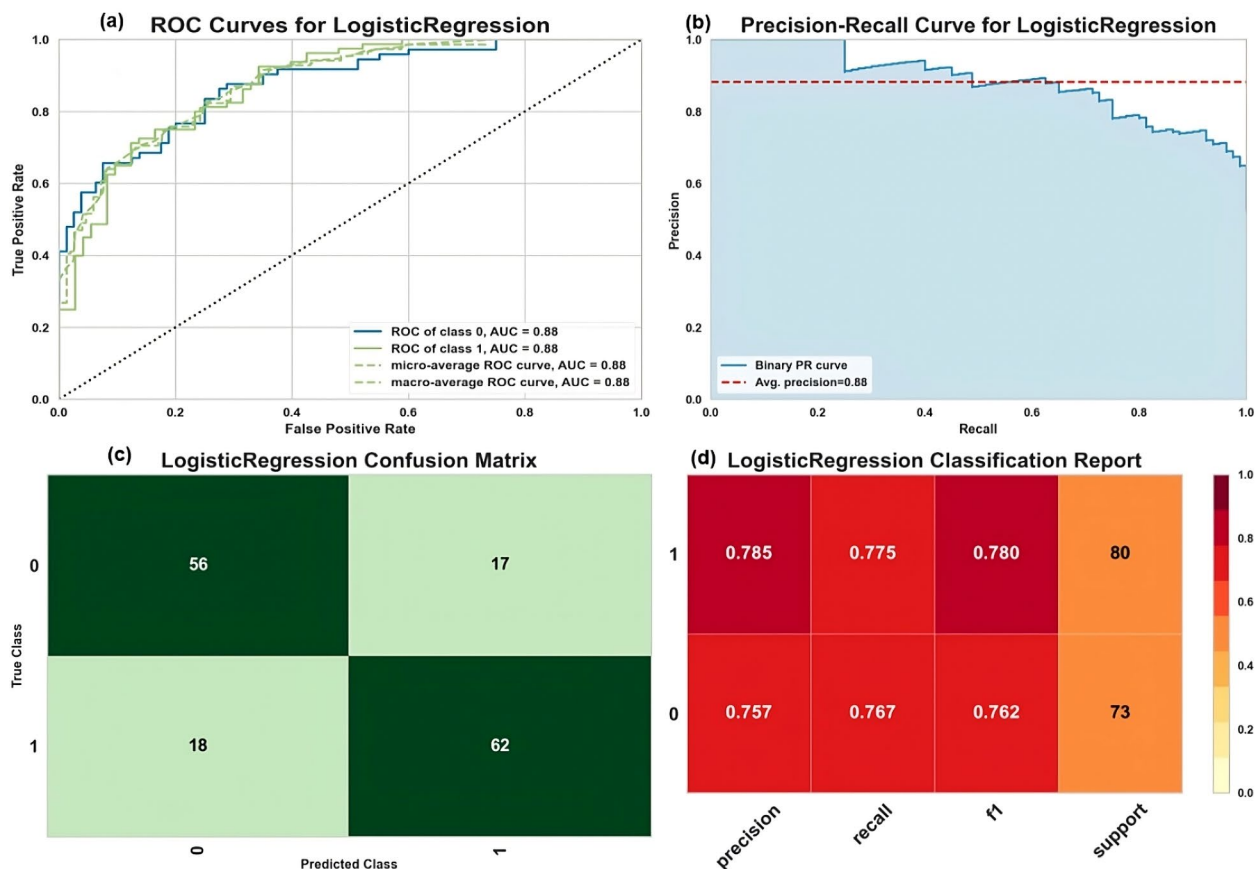
**Fig. 4** ROC curve (**a**), Precision-Recall Curve (**b**), Confusion Matrix (**c**), Classification Report (**d**) for classifying male and female individuals through LR Classifier

and female observations. The precision-recall curve in Fig. 4b demonstrates an average precision of 0.88, signifying the fair precision of the model. The confusion matrix (Fig. 4c), a tool for visualizing the dimensions for machine learning algorithm in binary or multi-class classification problems, compares true and predicted results for the test data using the best performed LR classifier. It was observed that a total of 118 observations (58 for class 0, females and 62 for class 1, males) by LR classifier were accurately predicted, along with 35 misclassifications (17 for class 0 and 18 for class 1), presenting overall accuracy of 87.40%. The classification report (presented in Fig. 4d), provides the value for precision, recall, and F1-score separately for both classes, along with the number of samples belonging to each class (73 females and 80 males). Class 0 (females) exhibit 0.757 precision, 0.767 recall, and 0.762 F1-score; and class 1 (males) shows 0.785 precision, 0.775 recall, and 0.780 F1-score on the test data for LR classifier.

The optimized LR classifier demonstrated an overall accuracy of 0.7712, an AUC value of 0.8777, and recall, precision, and F1-score of 0.7712, 0.7714, and 0.7713, respectively, along with a kappa and MCC metric score of 0.5418 (Supplementary Table S7) when internally

validated with test data. The feature importance plot (FIP), revealing the relative contribution of each feature in classification (Fig. 5), highlights "NASAL BREADTH" as the most influential in accurate predictions, followed closely by "PEL (R)", "CL (L)", "TOTAL LENGTH OF NASAL BRIDGE", "ELH (R)", "CL (R)", "THD (L)", "CW (L)", "PEB (R)", and "TAD (L)". Additionally, Fig. 6 presents a comprehensive feature importance plot for all dataset features.

External validation of the LR model using new data involved blind samples from both male and female individuals, predicting their respective classes based on different features. For external validation, ten percent of the samples used in model training, totaling fifty samples, were acquired. The outcomes of sample predictions, including the prediction score for each sample are provided in Supplementary Table S8. The model predicted eight samples incorrectly (4 males and 4 females) out of fifty for sex identification, resulting in an 84% accuracy rate in blind sample prediction.
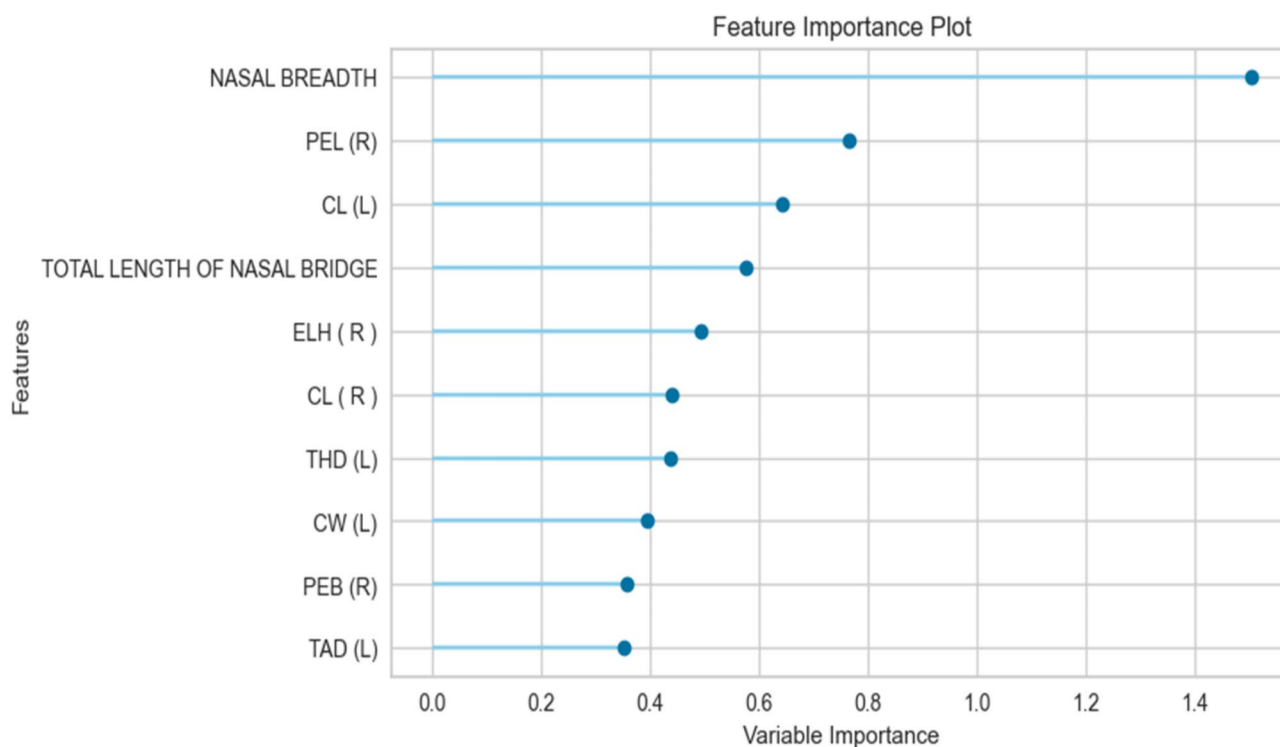
**Fig. 5** Feature importance plot specifying the most contributing features in dataset

## Discussion

Continuous advancement of existing methodologies and development of newer techniques is the prime requisite in order to enhance the degree of accuracy in personal identification or else narrow down the affliction of time and budget. The use of PyCaret machine learning makes experiments exponentially steadfast, robust and efficient [30]. Till now, binary logistic regression (BLR) and linear discriminant analysis (LDA) are the most commonly used statistical methods for sex estimation accuracy in forensic anthropology [31–34]. During the last few years, there has been an inclination in forensic anthropology for implementing machine learning (ML) classification algorithms [35] for identification of individuals using skeletal and morphological parameters.

In the present study, a comparison of fifteen machine learning classifiers was performed in the PyCaret library of Python framework, and it was found that logistic regression (LR) emerged as the predominant model for classification into male and female individuals, based on different anthropogenic measurements of ear and nose. The classification through LR achieved 86.75% accuracy for sex prediction, with "NASAL BREADTH" coming out to be the most influential features in accurate sex predictions, as evident from feature importance plot. On validating the LR classifier internally with test data, a good accuracy score of 0.7712 was obtained, along with good score for other metrics as well. Further, this model was validated externally with fifty unknown samples, achieving an accuracy rate of 84%.

It is evident that the present study received better accuracy, when compared to the other studies on ear measurements [10]. Here the sex predictive percentage accuracy came out to be, 76.3% from discriminant function analysis (DFA) and 76.2% from binary logistic regression (BLR). Similarly, sex classification accuracy from ear measurements as obtained from DFA among Sudanese population came out to be in the range of 60.5-72% [36].

Wu et al. [37] extracted four distinct features of nose from images to distinguish between male and female nose by applying image processing methods. The gender classification accuracy reaches upto 77% with 'curvature of nose wing' as the best gender classification parameter as depicted by linear discriminant analysis (LDA) [37]. Adamu et al. [38] determined sex using linear facial dimensions and angles among Hausas population of Nigeria. The facial variables (upper facial height, special upper height I, nasal width, lower facial width, mouth width and orbital width) give sex accuracy percentage upto 91.1%.

Pelvic bone is the most sexually dimorphic bone in the human body with the highest sex prediction accuracy of 100% from Diagnose Sexuelle Probiliste method [39]. However, it's not always necessary to get complete skeleton/innominate bone for identification and individualization. Thus, forensic anthropologists have to consider
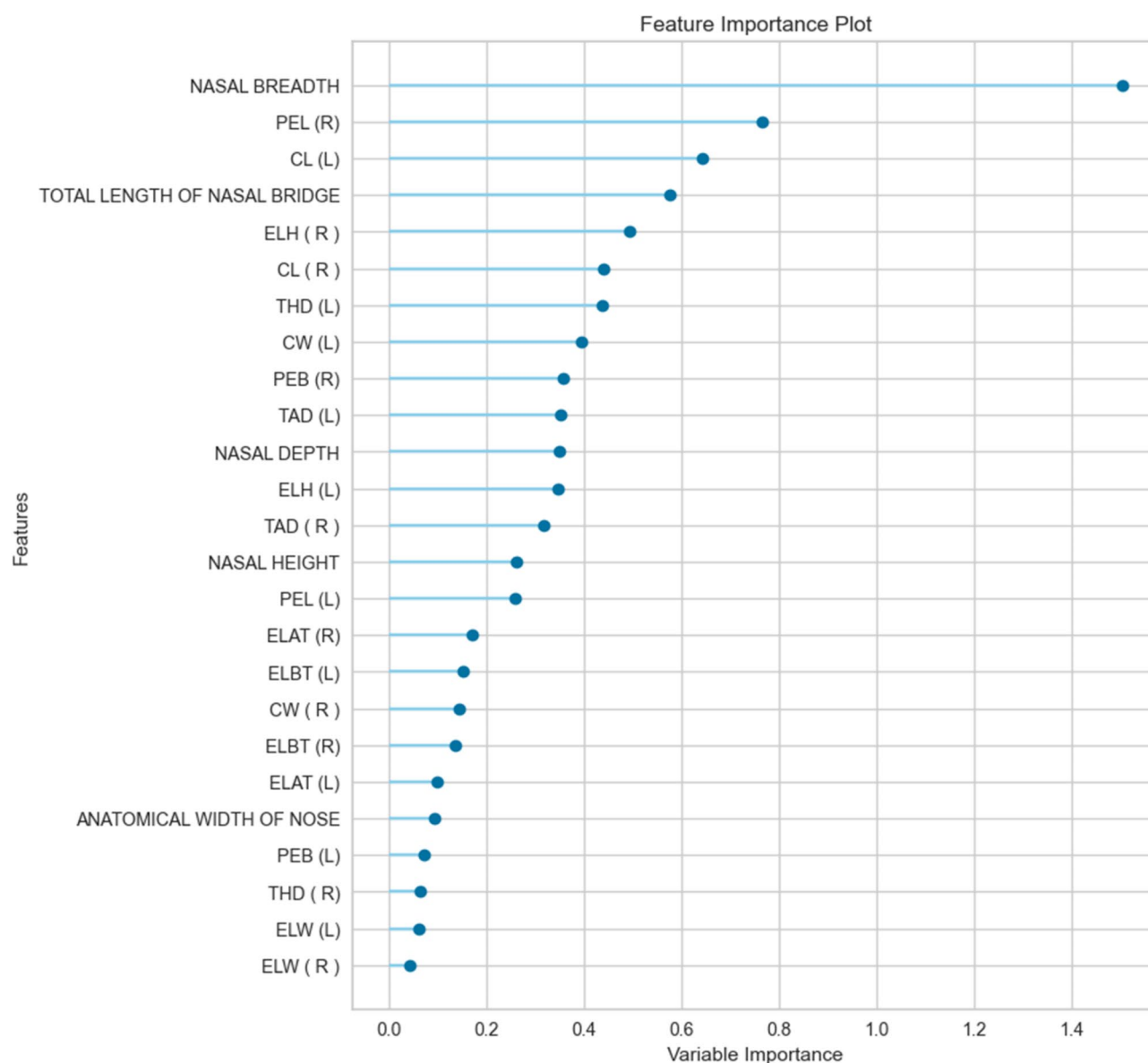
**Fig. 6** Feature importance plot for all the features used in dataset

other bodily traits for sex inference. Sex prediction from ear and nose using the present approach received comparable accuracy and reliability with that obtained from crania (Thai- 74.47%; French- 86% by DFA) [40] and long bones (femur- 81.5-84.5% by linear discriminant analysis) [41] (humerus-86.8% in Chinese; 92.4% in Japanese; 97.1% in Thais) (tibia- 93.8-95% by DFA) [41–43].

Our study contributes to forensic investigations since sex determination plays a significant role in constructing the victim and suspect biological profiles. Moreover, the study can provide standards for facial reconstruction and rejuvenation, plastic surgeries, rhinoplasty.

**Limitations of the study**

1. Sex classification accuracy depends on the ML algorithms used, and different methods may yield varying results. In this study, Logistic Regression gives the highest accuracy. Therefore, different studies may yield different results.
2. As the study has been conducted on one particular population i.e. a North Indian population, the same results may not be valid for other populations. However, the novel methodology used in this study can be utilized by other researchers for facial reconstruction, plastic surgeries, ergonomics, etc.
3. While sex differences exist in ear and nose morphology, they are not always strong enough

for perfect sex classification. These parameters may be used as corroborative evidence in forensic examinations [44].

## Conclusions and recommendations

The study has established the fact that individual's facial features like ear and nose can be helpful in estimating sex from living beings. The logistic regression (LR) classifier emerged as the top-performing model in PyCaret library, achieving the highest scores of 86.75% for sex prediction accuracy. Nasal breadth has been concluded as the most significant variable in accurate sex predictions, followed by right physiognomic ear length. As the machine learning model provides reasonable accuracy and reliability and the process is also time-saving, therefore, this can be used on large database from different populations for identification purposes. The study concludes that the novel approach for sex classification can be efficiently used in a variety of forensic examinations and crime scene investigation especially where there is a need for estimation of sex for personal identification. In the pursuit of achieving more accuracy and reliability, forensic researchers will continue to develop newer and better sex estimate procedures as well as reevaluate the ones that already exist. Thus, it has been suggested that such models can be used for establishing biological profiling from skeletal remains too.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s13104-025-07185-4.

Supplementary Material 1

## Declarations

## References
1. Plavcan JM. Sexual dimorphism in primate evolution. Am J Phys Anthropol. 2001;116:25–53. https://doi.org/10.1002/AJPA.10011.
2. Macho GA. Is sexual dimorphism in the femur a population specific phenomenon? Z Morphol Anthropol. 1990;78:229–42.
3. Britannica. The Editors of Encyclopedia, sexual dimorphism, Encyclopedia Britannica (2023). https://www.britannica.com/science/sexual-dimorphism (accessed March 23, 2024).
4. Wiskott L, Fellous JM, Krueger N, von der Malsburg C. Face recognition by elastic bunch graph matching. Proc Int Conf Image Process. 1997;1:129–32. https://doi.org/10.1109/ICIP.1997.647401.
5. Mello-Gentil T, Souza-Mello V. Contributions of anatomy to forensic sex estimation: focus on head and neck bones. Forensic Sci Res. 2022;7:11–23. https://doi.org/10.1080/20961790.2021.1889136.
6. Baryah N, Krishan K, Kanchan T. The development and status of forensic anthropology in India: A review of the literature and future directions. Med Sci Law. 2019;59:61–9. https://doi.org/10.1177/0025802418824834.
7. Vij K. Textbook of forensic medicine and toxicology: principles and practice. India: Elsevier; 2008.
8. Henneberg M, Simpson E, Stephan C. Human face in biological anthropology: craniometry, evolution and forensic identification. Hum Face. 2003;29–48. https://doi.org/10.1007/978-1-4615-1063-5_2.
9. Shi J, Samal A, Marx D. How effective are landmarks and their geometry for face recognition? Comput Vis Image Und. 2006;102:117–33. https://doi.org/10.1016/J.CVIU.2005.10.002.
10. Rani D, Krishan K, Kanchan T. A methodological comparison of discriminant function analysis and binary logistic regression for estimating sex in forensic research and case-work. Med Sci Law. 2022;63:227–36. https://doi.org/10.1177/00258024221136687.
11. Kaur T, Krishan K, Kaur P, Sharma SK, Kumar A. Application of tpsDig2 software in nasal Nngle measurements. J Craniofac Surg. 2020;31:319–25. https://doi.org/10.1097/SCS.0000000000006024.
12. Guleria A, Krishan K, Sharma V. Assessment of facial and nasal phenotypes: implications in forensic facial reconstruction. Arch Bio Sci (2025) (In Press).
13. Sarilita E, Rynn C, Mossey PA, Black S. Oscandar. Nose profile morphology and accuracy study of nose profile Estimation method in Scottish subadult and Indonesian adult populations. Int J Leg Med. 2018;132:923–31.
14. Sezgin N, Ersoy G. Metric and morphological features of the ear in sex classification. Egyptian J Forensic Sci. 2023;13(2023):44.
15. Bertillon A. R.W. McClaughry 1897 Signaletic instructions including the theory and practice of anthropometrical identification. J Anthropol Inst Great Br Irel 26 296 https://doi.org/10.2307/2842360.
16. Iannarelli AV. Forensic identification series: ear identification. California: Paramont; 1989.
17. Farkas LG, Kolar JC, Munro IR. Geography of the nose: a morphometric study. Aesthetic Plast Surg. 2005;10:191–223. https://doi.org/10.1007/BF01575292.
18. Brown A, Lamb E, Deo A, Pasin D, Liu T, Zhang W, Su S, Ueland M. The use of novel electronic nose technology to locate missing persons for criminal investigations. IScience. 2023;26:106353. https://doi.org/10.1016/J.ISCI.2023.106353.

19. Hsu BS. Comparisons of the five analytic reference lines of the horizontal lip position: their consistency and sensitivity. Am J Orthod Dentofac Ort104. 1993;355–60. https://doi.org/10.1016/S0889-5406(05)81333-2.
20. Cox NH, van der FPGM, Linden. Facial harmony. Am J Orthod. 1971;60:175–83. https://doi.org/10.1016/0002-9416(71)90033-9.
21. Springer IN, Wannicke B, Warnke PH, Zernial O, Wiltfang J, Russo PAJ, Terheyden H, Reinhardt A, Wolfart S. Facial attractiveness: visual impact of symmetry increases significantly towards the midline. Ann Plast Surg. 2007;59:156–62. https://doi.org/10.1097/01.SAP.0000252041.66540.EC.
22. Young P. Assessment of ideal dimensions of the ears, nose, and lip in the circles of prominence theory on facial beauty. JAMA Facial Plast Surg. 2019;21:199. https://doi.org/10.1001/JAMAFACIAL.2018.1797.
23. Sforza C, Laino A, D'Alessio R, Grandi G, Binelli M, Ferrario VF. Soft-tissue facial characteristics of attractive Italian women as compared to normal women. Angle Orthod. 2009;79:17–23. https://doi.org/10.2319/122707-605.1.
24. Kim DH, Yang SC, Kim H, Lee SS, Kim YS, Lozanoff S, Kwak DS, Lee UY. Regression analysis of nasal shape from juvenile to adult ages for forensic facial reconstruction. Leg Med. 2024;66:102363. https://doi.org/10.1016/J.LEGALMED.2023.102363.
25. Hall J, Froster-Iskenius U, Allanson J. Handbook of normal physical measurements. New York: Oxford University Press; 1989.
26. Singh IP, Bhasin MK. A manual of biological anthropology. Delhi: Kamla-Raj Enterprises; 2004.
27. Ulijaszek SJ, Kerr DA. Anthropometric measurement error and the assessment of nutritional status. Br J Nutr. 1999;82:165–77.
28. Barut C, Sevinc O, Sumbuloglu V. Evaluation of hand asymmetry in relation to hand preference. Coll Antropol. 2011;35:1119–24.
29. Krishan K, Kanchan T, Passi N. Estimation of stature from the foot and its segments in a sub-adult female population of North India. J Foot Ankle Res. 2011;4:24. https://doi.org/10.1186/1757-1146-4-24.
30. PyCaret. — Pycaret 3.0.4 documentation, (2020). https://pycaret.readthedocs.io/en/stable/ (accessed October 30, 2023).
31. Klales AR, Cole SJ. Improving nonmetric sex classification for Hispanic individuals. J Forensic Sci. 2017;62:975–80. https://doi.org/10.1111/1556-4029.13391.
32. Klales AR, Ousley SD, Vollner JM. A revised method of sexing the human innominate using Phenice's nonmetric traits and statistical methods. Am J Phys Anthropol. 2012;149:104–14. https://doi.org/10.1002/AJPA.22102.
33. Chatterjee PM, Krishan K, Singh RK, Kanchan T. Sex Estimation from the femur using discriminant function analysis in a central Indian population. Med Sci Law. 2020;60:112–21. https://doi.org/10.1177/0025802419900576.
34. Walker PL. Sexing skulls using discriminant function analysis of visually assessed traits. Am J Phys Anthropol. 2008;136:39–50. https://doi.org/10.1002/AJPA.20776.
35. Nikita E, Nikitas P. Sex estimation: a comparison of techniques based on binary logistic, probit and cumulative probit regression, linear and quadratic discriminant analysis, neural networks, and Naïve Bayes classification using ordinal variables. Int J Legal Med. 2020;134:1213–25. https://doi.org/10.1007/S00414-019-02148-4/TABLES/7.
36. Ahmed AA, Omer N. Estimation of sex from the anthropometric ear measurements of a Sudanese population. Leg Med. 2015;17:313–9. https://doi.org/10.1016/J.LEGALMED.2015.03.002.
37. Wu JH, Huang PS, Jian YJ, Fang JT. Gender classification by using human nose features. Biomed Eng (Singapore). 2016;28. https://doi.org/10.4015/S1016237216500368.
38. Adamu LH, Ojo SA, Danborno B, Adebisi SS, Taura MG. Sex determination using facial linear dimensions and angles among Hausa population of Kano State, Nigeria. Egypt J Forensic Sci. 2016;6:459–67. https://doi.org/10.1016/J.EJFS.2016.11.006.
39. Chapman T, Lefevre P, Semal P, Moiseev F, Sholukha V, Louryan S, Rooze M, Van Sint S, Jan. Sex determination using the probabilistic sex diagnosis (DSP: diagnose sexuelle Probabiliste) tool in a virtual environment. Forensic Sci Int. 2014;234:189e1. 189.e8.
40. Guyomarc'h P, Bruzek J. Accuracy and reliability in sex determination from skulls: A comparison of Fordisc® 3.0 and the discriminant function analysis. Forensic Sci Int. 2011;208. https://doi.org/10.1016/J.FORSCIINT.2011.03.011. 180.e1-180.e6.
41. Cuzzullin MC, Curate F, Freire AR, Costa ST, Prado FB, Daruge Junior E, Cunha E, Rossi AC. Validation of anthropological measures of the human femur for sex Estimation in Brazilians. Aust J Forensic Sci. 2022;54:61–74. https://doi.org/10.1080/00450618.2020.1729411.
42. Işcan MY, Loth SR, King CA, Shihai D, Yoshino M. Sexual dimorphism in the humerus: a comparative analysis of Chinese, Japanese and Thais. Forensic Sci Int. 1998;98:17–29. https://doi.org/10.1016/S0379-0738(98)00119-4.
43. Chatterjee PM, Krishan K, Singh RK, Kanchan T. Sex determination by discriminant function analysis using the human tibia in a central Indian population. Med Sci Law. 2019;59:171–9. https://doi.org/10.1177/0025802419845821.
44. Verma P, Sandhu HK, Verma KG, Goyal S, Sudan M, Ladgotra A. Morphological variations and biometrics of ear: an aid to personal identification. J Clin Diag Res: JCDR. 2016;10:ZC138. https://doi.org/10.7860/JCDR/2016/18265.7876.

## Publisher's note