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Original Research

Gender Estimation by Using Machine Learning Algorithms with Parameters Obtained from Direct Hand Graphs

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ABSTRACT

Objective: This study was conducted to make gender estimation with parameters obtained from direct hand graphs by using machine learning (ML) algorithms, which is a current issue in the field of health.

Methods: The study was conducted by retrospectively examining the X-ray images of 132 men and 126 women between the ages of 18 and 65 who had not undergone hand surgery or who did not have any pathologies in their hands. Proximal phalanx I length (PPI), distal phalanx I length (PDI), proximal phalanx V length (PP5), medial proximal phalanx V length (PM5), distal phalanx V length (PD5), metacarpal I length (M1) and metacarpal V length (M5) were measured on the images. Gender estimation was made by using the measurements obtained at the input of ML models.

Results: All the parameters obtained were found to be longer and significant in men when compared with women ($p<0.05$). In gender estimation with ML models, 0.88 Acc rate was obtained with Extra Tree Classifier algorithm and Acc rate of other algorithms was found to vary between 0.79 and 0.87.

Conclusion: As a result of the study, parameters obtained from X-ray hand graphs were found to have highly accurate gender estimation with ML algorithms. In cases where the identity of individuals needs to be predicted quickly and accurately, the analysis of hand radiographs obtained from X-rays and ML algorithms shows that the prediction time can be minimized and high accuracy can be achieved.

Keywords: hand, X-ray, machine learning algorithms, gender estimation

INTRODUCTION

Gender estimation is of great importance in forensic psychology since it has a critical role in the identification of unidentified individuals [1]. In cases when bodies have been decomposed or deformed due to crime and/or disasters, it is more complicated and difficult to identify a body. For this reason, it is very important to develop a method that can estimate the physical characteristics of individuals accurately [2].

It is a very complicated process to determine gender from morphological features of the human skeleton [3]. Today, although Deoxyribonucleic acid (DNA) technologies are considered as the method with the highest reliability in gender determination, they have disadvantages such as accessibility, consuming time, the need for qualified personnel and cost. For this reason, the use of methods such as machine learning (ML) algorithms, artificial neural networks and deep learning has recently become widespread in gender estimation [4, 5]. In addition to morphological determination, gender estimation can also be determined by using metric methods. Statistical methods used in metric methods are becoming more popular with the linear discriminant analysis of bones [6]. The most widely used metric method for gender estimation is ML. ML is an analysis method automating using specific algorithms and creating models with machines [7].

Besides being frequently used in the field of engineering, ML has also begun to be used in the field of health [8]. These algorithms are classified as supervised, unsupervised and reinforced. Supervised learning is algorithms matching the relationship between input and output; unsupervised learning is algorithms matching with the characteristics of data about which there is no information and reinforced learning is algorithms matching input data with desired characteristics [9]. In the literature, the most frequently used algorithms among ML models are decision tree (DT), logistic regression (LR), extra tree classifier (ETC), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA) [10, 11].

Skeletal system may differ according to gender with the effect of sex hormones [12]. So far, gender identification has been analysed by using different body parts such as femur [13, 14], patella [15], mandible [16, 17], calcaneus [18] and occipital condyle. In cases when dimorphic parts such as the pelvis and the skull are harmed and it is difficult to make an examination, it becomes a necessity to estimate gender with the less dimorphic parts of the human skeleton such as hand and foot bones [19, 20]. X-Ray is often used for taking images of the hand bones. X-ray is an easily applicable, fast and inexpensive method. Due to having a rapid imaging process and being widely accessible, hand X-ray images can be interpreted easily in a short time by radiologists [21].

Current studies in literature show that gender estimation from hand bones by using different methodologies has become widespread [22].

The hypothesis of this study is to demonstrate the success of gender estimation using ML with parameters obtained from X-ray images of the hand skeleton.

Main Points

- Can gender be estimated with parameters obtained from direct hand radiographs?
- What is the impact of Machine Learning Algorithms on gender prediction?
- Which parameters have a higher contribution when predicting gender from direct hand graphs?

MATERIAL AND METHODS

The study was conducted by retrospectively scanning the direct hand graphs of 132 men and 126 women between the ages of 18 and 65 who were admitted to İzmir Bakırçay University Çiğli Training and Research Hospital due to various health problems between 01.01.2020 and 20.07.2022. Individuals who had undergone hand surgery and those who had pathology, fracture and subluxation in their hands were excluded. The study was approved with İzmir Bakırçay University Çiğli Training and Research Hospital Non-Interventional Clinical Research Ethics Committee. The study was also conducted in accordance with the principles of the Declaration of Helsinki.

Image Acquisition and Processing

The images were obtained by retrospectively scanning the radiological archive system of the hospital. The images obtained were transferred to personal work station Horos DICOM Viewer (Version 3.0, United States of America) program in Digital Imaging and Communications in Medicine (DICOM) format. These images were measured by using the measurement console of the program (Figure 1).

Measurement parameters were:

- Proximal phalanx I length (PPI)
- Distal phalanx I length (PDI)
- Proximal phalanx V length (PP5)
- Medial phalanx V length (PM5)
- Distal phalanx V length (PD5)
- Metacarpal I length (M1)
- Metacarpal V length (M5)

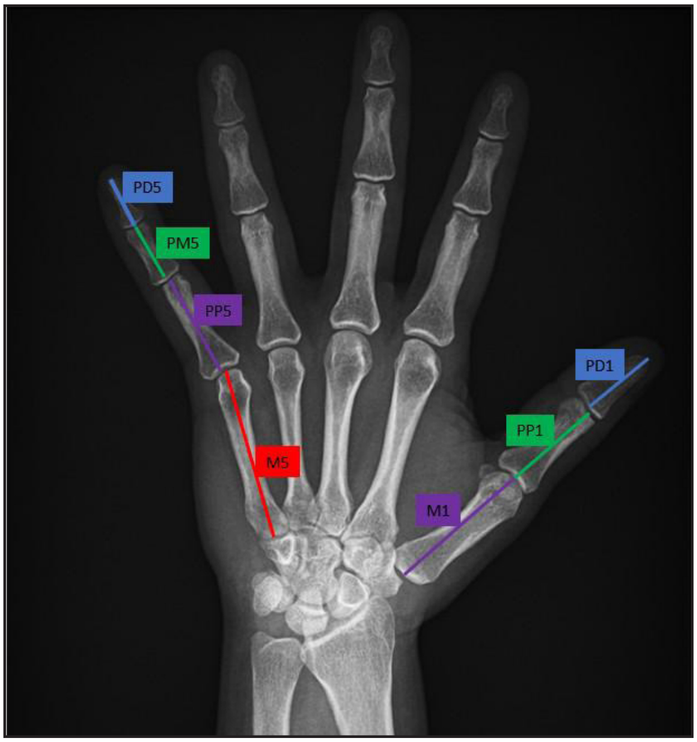


Figure 1. Demonstration of parameters

Machine Learning Algorithms Modelling Process

ML algorithms were modelled on a Monster Abra A7 model personal computer with 8 Gb Ram and i5 operating system. Python 3.9 programming language and scikit-learn 1.1.1 framework were preferred in modelling. Of the data used in modelling, 80% were used in training and 20% were used as test set. Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Logistic Regression (LR), Extra Tree Classifier (ETC), Decision Tree (DT), Random Forest (RF), Gaussian Naive Bayes (GaussianNB), K-Nearest Neighbors (k-NN) algorithms were used as ML models. Accuracy (Acc), Specificity (Spe), Sensitivity (Sen), F1 score (F1) values were used to evaluate the performance of models.

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

In addition, SHAP analyser of RF model was used to show the effect of parameters on gender.

Statistical Analyses

Basic statistical analyses were obtained by using Minitab 17 and Spss 21 programs, with p<0.05 value considered significant. Normality distribution of data was tested with Normality test Anderson Darling test. In descriptive statistics of data, mean±standard deviation was used for normally distributed data, while median (minimum-maximum) values were used for data which were not normally distributed. In the comparison of paired groups, Two Simple T test was used for normally distributed data, while Mann Whitney-U test was used for data which were not normally distributed. Correlation between parameters and the degree of correlation were shown with Pearson correlation test for normally distributed parameters, while they were shown with Spearman rho correlation test for parameters which were not normally distributed. ROC curve was used to show the power of the parameters.

RESULTS

In this study which was conducted on 312 men and 126 men between the ages of 18 and 65, it was found that M1, M5, PP5 parameters were normally distributed, while PP1, PD1, PD5, PM5 parameters were not normally distributed. Table 1 shows the descriptive statistics and comparison of normally distributed parameters in terms of gender. It was found that M1, M5, PP5 parameters were statistically longer in men when compared with women and significant difference was found between genders.

Table 1. Comparison and descriptive analysis results of normally distributed parameters in terms of gender

Parameters (cm)	Gender	Mean±Standard Deviation	P value*
M1	Male	4.839±0.367	0.000
	Female	4.353±0.341	
M5	Male	5.567±0.483	0.000
	Female	5.110±0.463	
PP5	Male	3.337±0.285	0.000
	Female	3.087±0.313	

Table 2 shows the descriptive statistics and comparison of non-normally distributed parameters in terms of gender. It was found that PP1, PD1, PM5, PD5 parameters were statistically longer in men when compared with women and significant difference was found between genders in these parameters (p<0.05).

Table 3 shows the correlation and correlation degree of normally distributed parameters in terms of gender. A very weak significant correlation was found in M1 parameter in terms of gender (p<0.05).

Table 2. Comparison and descriptive analysis results of non-normally distributed parameters in terms of gender

Parameters	Gender	Median (Min.-Max.)	P value**
Age (years)	Male	33 (18-65)	0.006
	Female	43 (18-65)	
PP1 (cm)	Male	3.055 (1.749-3.930)	0.000
	Female	2.779 (2.367-4.336)	
PD1 (cm)	Male	2.210 (1.289-2.813)	0.000
	Female	1.966 (1.376-4.336)	
PM5 (cm)	Male	1.840 (1.184-4.020)	0.000
	Female	1.634 (1.246-1.775)	
PD5 (cm)	Male	1.582 (1.150-2.155)	0.000
	Female	1.375 (1.109-1.775)	

**Mann Whitney-U test

Table 3. Pearson correlation test results of normally distributed parameters

Parameters	r/p	M1**	M5**	PP5**
M1*	r	0.190	0.124	0.053
	p	**0.033**	0.168	0.558
M5*	r	0.022	0.054	-0.039
	p	0.810	0.545	0.664
PP5*	r	0.096	0.113	0.042
	p	0.285	0.206	0.641

*Male, **Female

Table 4. Spearman rho correlation test results of non-normally distributed parameters

Parameters	r/p	PP1**	PD1**	PM5**	PD5**
PP1*	r	-0.017	-0.059	-0.090	0.003
	p	0.853	0.513	0.318	0.969
PD1*	r	-0.097	-0.057	-0.083	0.007
	p	0.280	0.528	0.358	0.936
PM5*	r	0.118	-0.058	0.107	0.038
	p	0.188	0.516	0.231	0.670
PD5*	r	-0.073	-0.048	0.090	0.149
	p	0.419	0.597	0.315	0.095

*Male, **Female

Table 4 shows the correlation and correlation degree of non-normally distributed parameters in terms of gender. No significant correlation was found in terms of gender as a result of statistical analysis (p>0.05).

Gender discrimination power of the parameters was shown with ROC analysis and the highest AUC value was obtained with M1 parameter (Figure 2).

Table 5 shows the AUC, Cut off, p, sen, spe values of the parameters.

As a result of ML modelling, the highest Acc value was found to be 0.88 with ETC algorithm (Table 6).

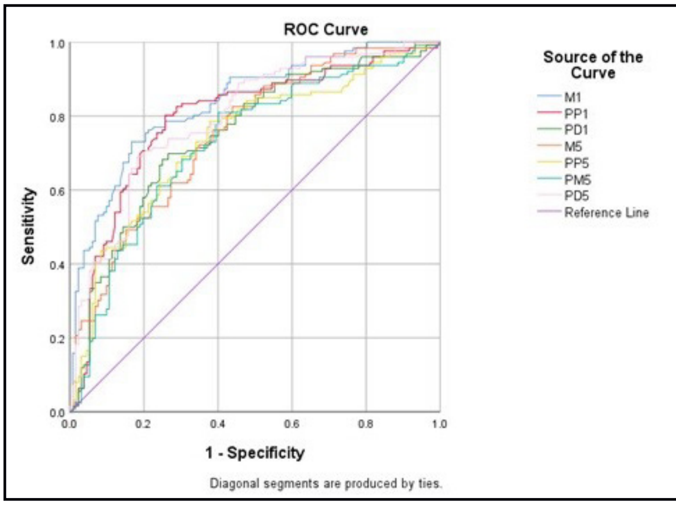


Figure 2. ROC curve

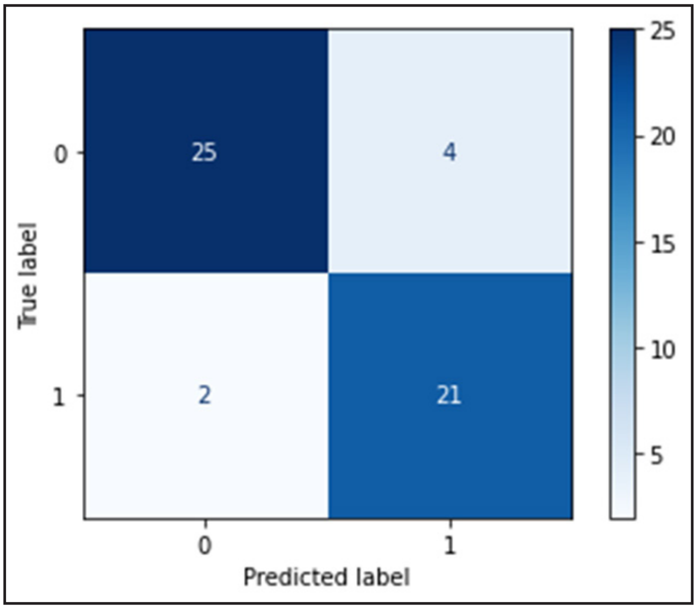
Table 5. ROC curve scores

Parameters	AUC (95%)	Cut off	p	Sen	Spe
M1	0.836 (0.788-0.885)	4.580	0.000	77.7	76.5
PP1	0.794 (0.738-0.851)	2.896	0.000	75.4	75.0
PD1	0.751 (0.691-0.811)	2.080	0.000	69.8	69.7
M5	0.750 (0.692-0.809)	5.320	0.000	67.5	66.7
PP5	0.738 (0.677-0.800)	3.237	0.000	69.0	68.9
PM5	0.726 (0.664-0.788)	1.737	0.000	68.3	68.2
PD5	0.797 (0.743-0.851)	1.462	0.000	73.8	73.5

Table 6. Performance values of machine learning models

Algorithms	Acc	Spe	Sen	F1
LDA	0.81	0.81	0.81	0.81
QDA	0.79	0.79	0.79	0.79
LR	0.83	0.83	0.83	0.83
ETC	0.88	0.89	0.88	0.88
DT	0.87	0.87	0.87	0.87
RF	0.87	0.87	0.87	0.87
GaussianNB	0.81	0.81	0.81	0.81
k-NN	0.83	0.83	0.83	0.83

Table 7. Confusion matrix table of Extra Tree Classifier algorithm



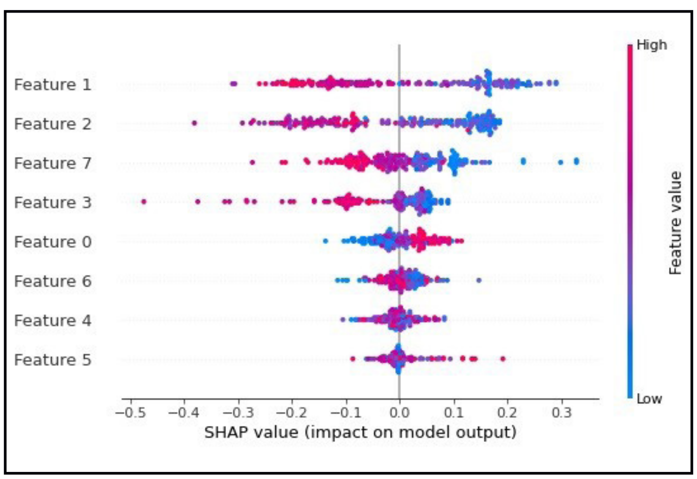


Figure 3. SHAP analyser (Feature 0: age, Feature 1: M1, Feature 2: PP1, Feature 3: PD1, Feature 4: M5, Feature 5: PP5, Feature 6: PM5, Feature 7: PD5).

Table 7 shows the confusion matrix of the highest Acc value as a result of ML modelling. As a result of the algorithm, 25 of 29 males and 21 of 23 females in the test set were estimated correctly.

Table 7 Confusion matrix table of Extra Tree Classifier algorithm
The effects of parameters on the overall result were evacuated by using SHAP analyser of RF algorithm and it was found that M1 parameter made the highest contribution to gender determination (Figure 3).

DISCUSSION

In this study in which gender estimation was made from anthropometric measurements of the hand by using ML models, 0.88 Acc rate was obtained with ETC algorithm. With SHAP analyser of RF algorithm, the highest three contributions in gender determination were found to be with M1, PP1, PD5 parameters, respectively. In addition, contribution of parameters was evaluated with ROC analysis and M1, PD5 and PD1 parameters were found to have the highest three contributions, respectively. As a result of the basic statistical analysis, all parameters were found to be longer and significant in men when compared with women ($p<0.05$).

In forensic anthropology, determining the identity of an individual with anthropometric methods is a common method because postmortem body integrity of individuals cannot be preserved most of the time and there arises a need for identification with anthropometric methods from the preserved/non-eroded skeletal remains of individuals. Natural disasters, wars and terrorist incidents are the most obvious examples of this situation. A critically important biomarker in determining an individual's identity is gender. Gender allows for the elimination of about half of the existing identity pool [8, 23, 24].

Using ML algorithms for identification of individuals, evaluation and interpretation of forensic evidence is important for obtaining accurate and quick results in forensic anthropology. Computer based applications have become very important with the digitalizing world. ML algorithms are also important in this respect and they stand out by giving more objective results than classical methods [8, 25, 26].

In a study Udayangani et al. conducted with the X-ray images of 40 women and 40 men, they found that M1, M5, PP1, PD1, PP5, PM5 and PD5 parameters were longer in men than in women and they reported differences in terms of gender ($p<0.05$) [27]. In a study Sandra et al. examined the X-ray images of 280 individuals, they found that PP1, PD1, PP5, PM5 and PD5 parameters were longer in men than in women and they reported significant difference in terms of gender ($p<0.05$) [28]. In a study conducted with the X-ray images of 30 women and 30 men in Turkish population, Ozsoy et al. found that PP1, PD1, PP5, PM5 and PD5 parameters were longer in men than in women and they reported significant difference in terms of gender ($p<0.05$) [29]. In a study conducted with the X-ray images of 100 Egyptians, Morsi et al. reported that M1, M5, PP1, PD1, PD5, PM5 and PD5 parameters were longer in men than in women [30]. In the present study we conducted with the X-ray images of 132 men and 126 women between the ages of 18 and 65 in Turkish population, we found that M1, M5, PP1, PD1, PD5, PM5 and PD5 parameters were longer in men than in women. In the present study, an Acc rate between 0.79 and 0.88 was obtained in gender estimation with ML modelling. The literature and our results show that these parameters used in hand anthropometry are longer in men and there is a significant difference in terms of gender. The difference of our study from other studies was that ML algorithms, a current methodology in the field of health, were used to make gender estimation instead of statistical analyses used in basic metric analyses. In addition, an important difference of ML algorithms used in the present study is being based on the principle of training 80% of data and testing 20% instead of training all of the data. A more realistic accuracy rate is found in this way.

Limitations

Small sample size, the fact that the study was conducted only on a specific population and the disadvantage of superposition since X-ray is a two-dimensional imaging technique are limitations of the study. We believe that working with a larger sample in the future will increase accuracy rate.

CONCLUSION

In the present study which was conducted to estimate gender from hand anthropometry, we believe that the data obtained from the first and fifth metacarpal bone and phalanx will make significant contributions to forensic anthropology.

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Informed Consent: All participants provided informed consent prior to their participatıon.

Conflict of interest: The authors declare that they have no conflict of interest.

Data Availability: Data sharing not applicable – no new data generated.

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Declarations: Conflict of interest The authors declare that they have no competing interests.

Ethical Approval : 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.

The study was conducted by retrospectively scanning the direct hand graphs of 132 men and 126 women between the ages of 18 and 65 who were admitted to İzmir Bakırçay University Çiğli Training and Research Hospital due to various health problems between 01.01.2020 and 20.07.2022.

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