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Sex and stature estimation from anthropometric measurements of the foot: linear analyses and neural network approach on a Turkish sample

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Abstract

Background For over a century, anthropometric techniques, widely used by anthropologists and adopted by medical scientists, have been utilized for predicting stature and sex. This study, conducted on a Eastern Turkish sample, aims to predict sex and stature using foot measurements through linear methods and Artificial Neural Networks. Our research was conducted on 134 medical students, comprising 69 males and 65 females. Stature and weight were measured in a standard anatomical position in the Frankfurt Horizontal Plane with a stadiometer of 0.1 cm precision. Measurements of both feet's height, length, and breadth were taken using a Vernier caliper, osteometric board, and height scale. The data were analyzed using SPSS 26.00.

Results It was observed that all foot dimensions in males were significantly larger than in females. Sex prediction using linear methods yielded an accuracy of 94.8%, with a stature estimation error of 4.15 cm. When employing Artificial Neural Networks, sex prediction accuracy increased to 97.8%, and the error in stature estimation was reduced to 4.07 cm.

Conclusions Our findings indicate that Artificial Neural Networks can work more effectively with such data. Using Artificial Neural Networks, the accuracy of sex prediction for both feet exceeded 95%. Additionally, the error in stature estimation was reduced compared to the formulas obtained through linear methods.

Keywords Sex determination, Stature estimation, Linear analysis, Artificial neural networks, Forensic anthropology

Background

In forensic sciences, the identification phase significantly involves determining sex and estimating stature. When identifying a victim or suspect, anthropological methods can reduce the number of potential matches, thereby saving human resources, time, and money. In both fatal and non-fatal incidents, the sex of a person can be determined using various data, including aspects of the body's appearance, parts of the skeleton and bones and numerous other factors (Ozden et al. 2005).

Morphological and metric techniques are prominent in identifying characteristics of living or deceased individuals. Metric techniques are based on measuring parts of the human body. For instance, the length of long

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bones in juveniles can determine age, while in adults, the lengths of long bones and extremities can predict stature and sex (Celbis and Agritmis 2006; Ubelaker and Khosrowshahi 2019). Morphological techniques, on the other hand, rely on the visual assessment of anatomical features (Krishan et al. 2016).

In the mass disasters, explosions, and terrorist attacks, body parts can help in the identification of victims. In such cases, primary identifiers like odontology, fingerprinting, or DNA can face delays or may sometimes be impractical. Developing a biological profile at the triage stage can provide valuable information for identification before antemortem data is available (de Boer et al. 2019). In disaster scenarios, the lower extremities, being more robust against taphonomic changes compared to upper extremities, are often found intact, especially feet which are usually protected within shoes and can withstand environmental factors more effectively (Singh et al. 2019). Additionally, in the identification of living individuals, foot anthropometry can be crucial evidence in evaluating footprints found at crime scenes or mass graves, often left by offenders (Hemy et al. 2013). These impressions can be made on hard surfaces by various substances, including dust, oil, blood, paint, and mud. If a link between a crime and a footprint is established, and if the footprint's dimensions can estimate the suspect's stature and sex, this can significantly contribute to the investigation in combination with other evidence from the scene (Reel et al. 2012). In this context, Özaslan et al. (2003) examined the relationship between different body parts and stature in the Turkish population, finding high R^2 values for foot stature in females, leading to regression equations for stature estimation (Özaslan et al. 2003). Özden et al. (2005) used foot and shoe measurements for stature estimation and sex determination in the Turkish population (Ozden et al. 2005). Krishan (2008) and Awais et al. (2018) carried out studies on stature estimation from footprints and sex determination respectively, in Indian Gujjar and Pakistani Punjab populations (Krishan 2008; Awais et al. 2018).

The results of stature and sex estimation studies are known to be highly population-specific, and the necessity of developing population-specific standards while creating a biological profile is well recognized (Işcan 2005). While there have been studies on stature and sex estimation based on foot measurements in the Western Turkish population (Özaslan et al. 2003; Ozden et al. 2005; Zeybek et al. 2008; Atamturk 2010), no such study exists for the Eastern Turkish population. Moreover, while some sex determination studies have utilized artificial neural networks in various anthropometric measurements (Navega et al. 2015; Kartal et al. 2022; Senol et al. 2023), there are very few studies focused on stature estimation in the literature. Specifically, no study employing artificial neural networks on foot measurements has been found.

The purpose of this study is to predict stature and sex in the Eastern Turkish population using foot measurements through Linear Discriminant and Regression Analyses. Additionally, Artificial Neural Networks have been employed to assess the data.

Methods

In our study, measurements were conducted on students at our faculty of medicine. After obtaining their informed consent, a total of 134 volunteers, comprising 69 males and 65 females, were included in the research. We excluded individuals with deformities that could affect stature or lower extremity length, such as spinal, upper extremity, and lower extremity deformities, diseases of long bones and spine, or those who had undergone surgical procedures on these bones. Additionally, those over 65 years of age were not included in the study. The lower age limit was set at 21 years, considering that the median age for achieving full stature in men is around 21.2 years, and growth can continue up to 23.5 years, ensuring the participants were likely at their full adult stature (Roche and Davila 1972). Data regarding the participants age, sex, and weight were recorded. All students were from Malatya, a city in Eastern Turkey, and its surrounding cities.

Stature measurement

Stature were measured with the individual in an upright position, eyes looking forward, standing with the back against a flat surface, and the body in an anatomical position as shown in Fig. 1. The distance from the surface in contact with the feet to the vertex of the head was measured using a stadiometer with 0.1 cm precision. In the Frankfurt horizontal plane, the lowest point of the orbital margin aligns with the tragion, the deepest point of the notch above the tragus of the ear. In the Frankfurt horizontal plane, the line of sight is horizontal to the ground and perpendicular to the head's sagittal plane (İşcan and Steyn 2013). Considering diurnal variations in stature, measurements were taken between 09:00 and 10:00 AM (Krishan and Vij 2007).

Measurement error and reliability

All measurers received initial training in technique from the author OC. Measurements were taken by the other authors, MEP and BBÖ. The specified dimensions were measured separately for each foot. To assess intra-observer and inter-observer error, measurements were repeated on a randomly selected group of 30 individuals.

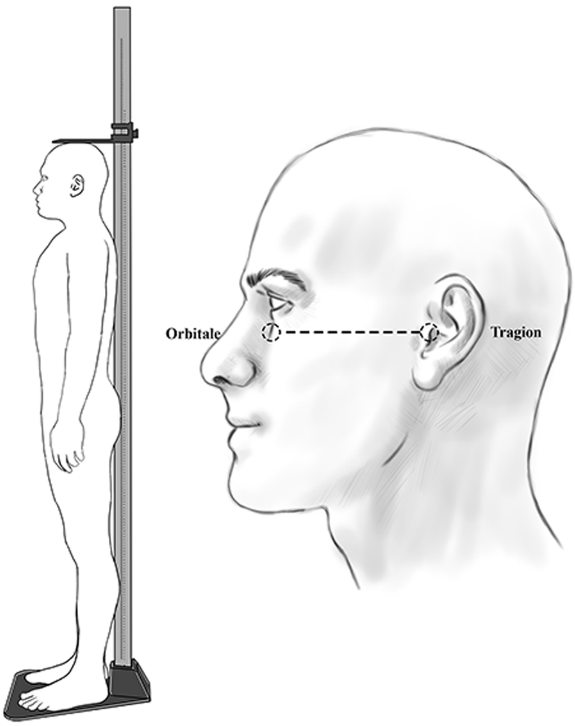

Fig. 1 Measurement of stature using a Stadiometer (in the Frankfurt Horizontal Plane). (Illustrations by MEP)

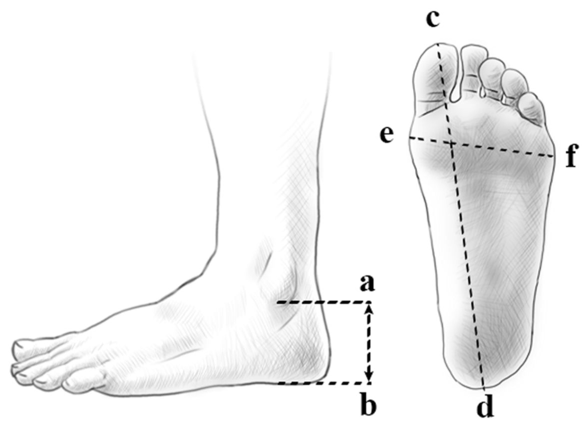

Fig. 2 Foot measurements;» Foot Stature (FH) (**a**-**b**),» Foot Length (FL) (**c**-**d**),» Foot Breadth (FB) (**e**–**f**). (Illustrations by MEP)

Technical Error of Measurement (TEM), relative Technical Error of Measurement (rTEM, %), and reliability coefficient (R) were calculated. Acceptable levels of intra-observer and inter-observer rTEM for beginner anthropometrists are < %1.5 and < %2.0, respectively (Geeta et al. 2009). An R value greater than 0.95 indicates that the measurement error is negligible and the technique can be considered sufficiently precise (Arroyo et al. 2010).

Measured foot dimensions

Right-Left Foot Stature (RFH-LFH)

Foot stature is the distance between the lower alignment of the lateral malleolus and the heel. Foot osteometric board measurements were taken with the lower extremity in a relaxed position (Fig. 2).

Right-Left Foot Length (RFL-LFL)

Foot length is the maximum distance between the frontmost (acropodion) and rearmost part of the heel (pternion). Measurements were taken with the participant in a seated position and the foot elevated to avoid influence from body weight, using a Vernier caliper with 0.05 mm precision (Fig. 2).

Right-Left Foot Breadth (RFB-LFB)

Foot breadth is the distance between the protrusions made by the 1st and 5th metatarsals on either side of the foot. Measurements were taken with the participant in a seated position and the foot elevated, using a Vernier caliper with 0.05 mm precision (Fig. 2).

Statistical analysis

Quantitative data were presented as median (min–max), mean ± standard deviation, while qualitative data were presented as number (percentage). Descriptive statistics for all measurements were analyzed, and parameters were compared between sexes. Normal distribution conformity was tested using the Shapiro–Wilk and Kolmogorov–Smirnov tests. After verifying normal distribution, quantitative data were analyzed using independent sample t-tests, paired samples t-tests, linear regression analysis for stature estimation, and univariate and multivariate linear discriminant analyses for sex differentiation. Non-normally distributed data were evaluated with the Mann–Whitney U Test. The unstandardized coefficients and beta values of linear regression functions, along with mean absolute error (MAE) and root mean squared error (RMSE) values, were obtained. For discriminant functions, unstandardized and Fisher's linear coefficients, group centroids, accuracy, and F1 values were derived. A p-value of < 0.05 was considered statistically significant.

In addition to linear methods, Artificial Neural Networks (ANNs) were also used for stature estimation and sex determination in our study. ANNs, a form of artificial intelligence, mimic the decision-making process of the human brain (Tu 1996). Unlike regression or discriminant analysis, decisions are made using neurons and synapses, as in the brain, rather than formulas. Optimal combinations are found by optimizing synaptic weights through the backpropagation method, and the resulting ANN structure is used for decision-making in classification and regression problems (Tu 1996; du Jardin et al. 2009; Etli et al. 2019).

Ten-fold cross-validation was employed to assess the performances of the Linear Regression, Linear Discriminant, and ANN models. In tenfold cross-validation, the training data are randomly divided into 10 folds of approximately equal size. In each step of the cross-validation process, 9 folds are utilized as training data, and the model developed is then tested on the remaining fold. This process is iterated 10 times, with each fold being used once as a test set (Czibula et al. 2016; Calder et al. 2022). Analyses were conducted using IBM SPSS Statistics 26.0.

Results

The intra-observer rTEM for all measurements was found to be below 1.5%, and the inter-observer rTEM was below 2.5%. The intra-observer and inter-observer R value for all measurements was found to be above 95%. Based on these results, the measurement method can be considered consistent and reliable. Values for measurement error are provided in Table 1.

A descriptive statistical analysis and t-test of all measurements in male and female groups are shown in Table 2. It was observed that all measurements were higher in males compared to females. All measurement averages were significantly higher in the male group compared to the female group. There was no significant difference observed in the ages between the male and female groups.

In females, the FL on the right side was significantly longer ($p < 0.05$) than on the left side. Regarding FB, no significant differences were observed between the two feet in either sex. However, for FH, it was significantly larger ($p < 0.05$) on the left side in males. The results of the paired samples t-test for differences in measurements of both feet in females and males are presented in Table 3.

The cross-validated results of the linear discriminant analysis are shown in Table 4. For univariate analysis, the best variables for sex differentiation

Table 1 Intraobserver and interobserver error values

	Intra-Observer			Inter-Observer		
Measurements	TEM	rTEM (%)	R	TEM	rTEM (%)	R
RFH	0.067	1.378	0.984	0.095	1.943	0.968
RFL	0.126	0.491	0.991	0.184	0.720	0.979
RFB	0.100	1.074	0.971	0.106	1.145	0.967
LFH	0.068	1.309	0.988	0.082	1.569	0.982
LFL	0.146	0.571	0.989	0.163	0.636	0.985
LFB	0.065	0.690	0.988	0.114	1.228	0.963

TEM Technical error of measurement, *rTEM* Relative technical error of measurement, *R* Reliability coefficient, *RFH* Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Table 2 Descriptive statistics of all measurements (in cm) and ages for males and females

	Male ($n = 69$)					Female ($n = 65$)					*p* values
	Min	Max	Mean	Median	S.D	Min	Max	Mean	Median	S.D	
Stature	162.80	188.00	176.40		5.79	150.40	177.70	162.02		6.55	**0.000***
Age	21	30	-	22	1.92	21	30	-	22	1.53	0.844**
RFH	3.80	5.90	4.81	-	0.54	2.70	4.70	3.71	-	0.48	**0.000***
RFL	23.10	28.10	25.57	-	1.13	20.69	25.30	22.98	-	1.03	**0.000***
RFB	8.00	10.10	9.05	-	0.44	6.70	8.70	7.90	-	0.44	**0.000***
LFH	3.50	6.10	4.87	-	0.63	2.80	4.80	3.74	-	0.46	**0.000***
LFL	23.10	27.90	25.55	-	1.13	20.90	25.20	22.89	-	1.04	**0.000***
LFB	8.00	10.10	9.07	-	0.46	6.90	9.00	7.92	-	0.45	**0.000***

S.D. Standard deviation, *RFH* Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Significance level at $p < 0.05$, *Independent samples t test, **Mann Whitney U Test

Table 3 Evaluation of differences in right and left foot measurements using the paired samples t-test

	Measurements	Mean	S.D	*p* value
Female (*n* = 65)	RFH—LFH	-0.02569	0.15	0.160*
	RFL—LFL	0.08862	0.26	**0.009***
	RFB—LFB	-0.02000	0.21	0.441*
Male (*n* = 69)	RFH—LFH	-0.06594	0.25	**0.034***
	RFL—LFL	0.01884	0.32	0.628*
	RFB—LFB	-0.02029	0.23	0.462*

S.D. Standard deviation, *RFH* Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Significance level at $p < 0.05$, *Paired samples t test

were found to be RFB (90%) and RFL (87.4%), respectively. For multivariate analysis, the sex differentiation results were RFH/RFL/RFB (94.0%) and LFH/LFL/LFB (94.8%), respectively. When using the coefficient values obtained from discriminant analysis, along with the height, length, and breadth of the right and left feet, the formulas for sex differentiation are as follows (Discriminant score less than sectioning point is female):

$$\text{Sex} = -22.196 + 0.987\text{RFH} + 0.294\text{RFL} + 1.276\text{RFB}$$
(Sectioning point = 0.000)

$$\text{Sex} = -22.042 + 0.891\text{LFH} + 0.355\text{LFL} + 1.126\text{LFB}$$
(Sectioning point = 0.000)

In sex determination using ANNs, the cross-validated accuracy rates for sex determination based on measurements of both feet are 96.3% and 97.8%, respectively (Table 5). Graphic Representation of ANNs which were Established and Used for Sex Estimations are given in Supplement 1, 2.

The coefficients and beta values obtained from the Linear Regression analysis are presented in Table 6. When examining the linear regression analyses separately for each sex, the R^2 values after cross-validation for the right foot were found to be 0.449 for males and 0.577 for females, respectively, and for the left foot, they were 0.454 for males and 0.612 for females. The cross-validated results of the Linear Regression analysis are summarized in Table 7. When using the coefficient values obtained from multiple regression analysis, along with the height,

Table 4 Univariate and multivariate discriminant analysis classification results

Variables	Unstandardized Coefficient	Fisher's Linear Discriminant Function		Group Centroids		Classification Results (tenfold Cross-Validated)			
		Male	Female	Male	Female	Male (%)	Female (%)	Overall (%)	F1 score (%)
Univariate Analysis									
RFH	1.945	18.195	14.041	1.036	-1.100	82.6	84.6	83.6	83.8
Constant	-8.317	-44.405	-26.772						
RFL	0.924	21.852	19.636	1.163	-1.234	85.5	89.2	87.3	87.4
Constant	-22.476	-280.067	-226.336						
RFB	2.274	46.795	40.851	1.268	-1.346	91.3	87.7	89.6	90.0
Constant	-19.309	-212.362	-162.053						
LFH	1.804	15.854	12.152	0.996	-1.057	78.3	87.7	82.8	82.4
Constant	-7.795	-39.299	-23.424						
LFL	0.918	21.533	19.289	1.186	-1.259	84.1	86.2	85.1	85.3
Constant	-22.272	-275.788	-221.496						
LFB	2.212	44.353	38.730	1.233	-1.309	89.9	81.5	85.8	86.7
Constant	-18.822	-201.764	-154.065						
Multivariate Analysis									
RFH	0.987	8.383	5.116	1.606	-1.705	91.3	96.9	94.0	94.0
RFL	0.294	15.522	14.549						
RFB	1.276	25.555	21.329						
Constant	-22.196	-334.898	-261.616						
LFH	0.891	7.792	4.894	1.578	-1.675	92.8	96.9	94.8	94.8
LFL	0.355	15.733	14.578						
LFB	1.126	22.678	19.017						
Constant	-22.042	-323.495	-252.012						

RFH Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, LFL Left foot length, *LFB* Left foot breadth

Table 5 Results of sex determination using ANNs

Classification Results*

RFH + RFL + RFB				**LFH + LFL + LFB**			
	Estimated Sex				**Estimated Sex**		
Real Sex	**Male**	**Female**	**Accuracy**	**Real Sex**	**Male**	**Female**	**Accuracy**
Male	65	4	94.2%	Male	68	1	98.6%
Female	1	64	98.5%	Female	2	63	96.9%
Overall			96.3%	Overall			97.8%
			F1 = 96.3%				F1 = 97.8%

RFH Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

* All analyses were performed with tenfold cross-validation

Table 6 Linear regression coefficients used to calculate stature

Variables

	Constant	**RFH**	**RFL**	**RFB**		**Constant**	**LFH**	**LFL**	**LFB**
Male	99.643	2.721	3.507	-2.875	Male	92.903	1.531	3.712	-2.075
Beta		0.255	0.685	-0.217	Beta		0.166	0.726	-0.163
Female	49.051	3.247	5.007	-1.789	Female	45.608	3.440	5.035	-1.478
Beta		0.239	0.785	-0.121	Beta		0.243	0.801	-0.101

RFH Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Table 7 Multiple linear regression equations and ANN models with respect to males, females and results combined

Regression Results*

RFH + RFL + RFB						**LFH + LFL + LFB**					
Linear Regression	**R**	**R^2**	**Adj. R^2**	**MAE (cm)**	**RMSE (cm)**	*Linear Regression*	**R**	**R^2**	**Adj. R^2**	**MAE (cm)**	**RMSE (cm)**
Male	0.670	0.449	0.424	3.31	4.27	Male	0.674	0.454	0.429	3.32	4.25
Female	0.760	0.577	0.556	3.45	4.22	Female	0.782	0.612	0.593	3.38	4.05
Overall	0.893	0.798	0.793	3.38	4.25	Overall	0.898	0.807	0.802	3.36	4.15
Neural Network	**R**	**R^2**	**Adj. R^2**	**MAE (cm)**	**RMSE (cm)**	*Neural Network*	**R**	**R^2**	**Adj. R^2**	**MAE (cm)**	**RMSE (cm)**
Male	0.686	0.471	0.447	3.22	4.18	Male	0.689	0.475	0.451	3.21	4.16
Female	0.774	0.600	0.580	3.36	4.11	Female	0.793	0.628	0.610	3.22	3.96
Overall	0.898	0.807	0.803	3.29	4.15	Overall	0.902	0.814	0.810	3.21	4.07

R Pearson's correlation coefficient, *R^2* Coefficient of determination, *MAE* Mean absolute error, *RMSE* Root mean squared error, *RFH* Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth, *LFH* Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

* All analyses were performed with tenfold cross-validation

length, and breadth of the right and left feet, the formulas for stature estimation are as follows:

Stature(Male) = 99.643 + 2.721RFH + 3.507RFL − 2.875RFB // 92.903 + 1.531LFH + 3.712LFL − 2.075LFB.

Stature(Female) = 49.051 + 3.247RFH + 5.007RFL − 1.789RFB // 45.608 + 3.440LFH + 5.035LFL − 1.478LFB.

Stature estimation using ANNs was analyzed separately for males and females. The R^2 values after cross-validation for the right foot were 0.471 for males and 0.600 for females, and for the left foot, they were 0.475 for males and 0.628 for females. The results of the ANNs are summarized in Table 7. Graphic Representation of Artificial Neural Networks which were established and used for stature estimations are given in Supplement 3, 4, 5 and 6.

The parameter estimates for ANNs used in sex and stature prediction are shown in Tables 8, 9, 10, 11, 12 and 13.

Table 8 ANN parameter estimates used for sex prediction from right foot measurements

Predictor	Predicted				
	Hidden Layer			Output Layer	
Input Layer	**H(1:1)**	**H(1:2)**	**H(1:3)**	**Female**	**Male**
(Bias)	-0,209	-0,209	0,207		
RFH	-0,329	-1,869	-0,316		
RFL	0,025	-0,779	0,279		
RFB	-0,253	-1,869	-0,338		
Hidden Layer					
(Bias)				-0,430	0,164
H(1:1)				0,612	-0,503
H(1:2)				2,953	-2,869
H(1:3)				0,331	-0,590

RFH Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth

Table 9 ANN parameter estimates used for sex prediction from left foot measurements

Predictor	Predicted				
	Hidden Layer			Output Layer	
Input Layer	**H(1:1)**	**H(1:2)**	**H(1:3)**	**Female**	**Male**
(Bias)	0,677	-1,447	-0,148		
LFH	-1,818	-2,656	-1,765		
LFL	-0,298	-1,145	-0,676		
LFB	-1,410	-2,639	-0,606		
Hidden Layer					
(Bias)				0,177	-0,480
H(1:1)				1,021	-0,926
H(1:2)				2,378	-2,567
H(1:3)				1,325	-1,346

LFH Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Table 10 ANN parameter estimates used for stature estimation in females from right foot measurements

Predictor	Predicted	
	Hidden Layer	Output Layer
Input Layer	**H(1:1)**	**Stature**
(Bias)	0,402	
RFH	-0,367	
RFL	-1,003	
RFB	0,061	
Hidden Layer		
(Bias)		0,049
H(1:1)		-1,051

RFH Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth

Table 11 ANN parameter estimates used for stature estimation in males from right foot measurements

Predictor	Predicted				
	Hidden Layer				Output Layer
Input Layer	**H(1:1)**	**H(1:2)**	**H(1:3)**	**H(1:4)**	**Stature**
(Bias)	0,309	-0,128	0,433	0,213	
RFH	0,036	0,489	0,036	0,328	
RFL	-0,404	0,707	0,025	-0,460	
RFB	-0,193	-0,515	-0,210	-0,462	
Hidden Layer					
(Bias)					0,213
H(1:1)					-0,790
H(1:2)					0,870
H(1:3)					0,098
H(1:4)					-0,197

RFH Right foot stature, *RFL* Right foot length, *RFB* Right foot breadth

Table 12 ANN parameter estimates used for stature estimation in females from left foot measurements

Predictor	Predicted		
	Hidden Layer		Output Layer
Input Layer	**H(1:1)**	**H(1:2)**	**Stature**
(Bias)	-0,055	-0,261	
LFH	0,564	0,307	
LFL	0,668	-0,556	
LFB	0,006	0,267	
Hidden Layer			
(Bias)			-0,046
H(1:1)			1,203
H(1:2)			-0,418

LFH Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Table 13 ANN parameter estimates used for stature estimation in males from left foot measurements

Predictor	Predicted			
	Hidden Layer			Output Layer
Input Layer	**H(1:1)**	**H(1:2)**	**H(1:3)**	**Stature**
(Bias)	-1,103	0,241	-0,039	
LFH	0,795	-0,446	0,446	
LFL	0,553	0,381	-0,464	
LFB	-0,796	0,296	-0,629	
Hidden Layer				
(Bias)				0,830
H(1:1)				1,504
H(1:2)				0,962
H(1:3)				-0,367

LFH Left foot stature, *LFL* Left foot length, *LFB* Left foot breadth

Discussion

In our study, the analyses conducted for sex and stature prediction from foot measurements revealed that linear statistical methods achieved a 94.8% accuracy rate in sex prediction and a 4.15 cm error (RMSE) in stature prediction. When artificial intelligence algorithms were employed, these rates were further improved to 97.8% accuracy in sex prediction and a 4.07 cm error (RMSE) in stature prediction.

Literature review indicates that the pelvis and skull are the most reliable indicators for sex differentiation, and long bones yield better results for stature prediction, with a focus mostly on these bones (Hasegawa et al. 2009; İşcan and Steyn 2013) Differences between males and females in long bones (humerus, radius, ulna, femur, tibia, and fibula) are distinct and provide good results in stature and sex prediction, though the dimorphism is not as pronounced as in the pelvis and skull (Trotter and Gleser 1958; Celbis and Agritmis 2006). In cases of accidents, disasters, terrorist attacks, or bombings, human remains might be fragmented or largely missing. In such situations, assessing sex and stature on fragmented or incomplete remains presents certain challenges. If the skull, pelvis, and long bones have lost significant characteristics in forensic anthropological examination, it might be necessary to utilize the existing features of the body remains (Kjellström 2004; İşcan and Steyn 2013).

Foot measurements for sex determination and stature estimation have been a research topic from past to present in literature. Krishan et al. (2011) in their study conducted in North India, investigated the effectiveness of hand and foot measurements in sex differentiation. Models created using linear methods achieved 86–88.5% accuracy from foot breadth and 82–83.5% accuracy from foot length for sex differentiation (Krishan et al. 2011). Sen et al. (2011) in their study on an indigenous population in India found that foot breadth and length measurements, along with the foot index, could be used for sex determination with 84% accuracy (Sen et al. 2011). In Turkey, Zeybek et al. (2008) demonstrated that foot measurements could differentiate sex with 95–96% accuracy and estimate stature with a 3.8 cm error using Logistic Regression methods. They proposed that the results obtained from foot measurements would be consistent with similar populations (Zeybek et al. 2008). Although the results of Linear Discriminant Analysis for sex differentiation from foot measurements, with 94.0–94.8% accuracy and a stature estimation error of 4.15 cm (RMSE), were found to be quite similar to our findings, it is important to note that our current results have been tenfold cross-validated, which suggests they may be more generalizable for the study group. Notably, predictions made using ANNs in our study provided better results compared to Linear Analyses.

It is known that extremity width measurements provide better sex differentiation compared to length measurements (Šlaus and Tomičić 2005; Khan et al. 2020). This can be explained by bone remodeling mechanisms that lead to more cortical bone development in males than females during puberty (Black III 1978). This difference in cortical bone development primarily affects width and circumference measurements. Many studies suggest that epiphyseal measurements and mid-shaft circumferences are more reliable indicators of sex, as functional effects of weight and muscle structure concentrate on these characteristics of long bones. Considering the correlation of maximum foot breadth with the cortical bone widths of the metatarsals, foot measurements alone can be a good indicator for sex differentiation with up to 90% accuracy (Zeybek et al. 2008).

In forensic sciences, the dimensions of the lower extremities hold significant value, especially for stature estimation. Previous studies have demonstrated that the bones of the lower extremities are more reliable for stature estimation compared to those of the upper extremities (Ozaslan et al. 2012). Krishan and Sharma (2007) conducted a study on stature estimation using hand and foot measurements in the Rajput population of India. They found that foot length showed a correlation above 0.70 for both men and women. Using linear regression, stature estimation from foot length had an error range of 4.38–3.50 cm, which decreased to 3.02–2.98 cm when foot breadth was included (Krishan and Sharma 2007). In another study, Singh et al. (2019) found that foot length alone had an R^2 value of up to 0.399 for stature estimation in men, and the error rate reduced from 4.704 cm to 4.642 cm when other foot measurements were included (Singh et al. 2019). Hemy et al. (2013) in their study on the Western Australian population, demonstrated that foot length alone correlated with stature above 0.70, with linear methods resulting in an estimation error of 5.064–4.673 cm (Hemy et al. 2013). The literature emphasizes that the standard error of multiple regression equations provides more accurate values for stature estimation compared to linear regression equations (Zeybek et al. 2008). It can be said that foot length, in correlation with other foot measurements, demonstrates a correlation above 0.70 with stature, making it a reliable indicator for stature estimation.

Different aspects of the foot have been explored in various studies for the accurate determination of sex and stature. In this context, footprints, which can be obtained from crime scenes, are significant for creating biological profiles of victims and perpetrators in criminal investigations. Atamtürk (2010) reported a sex differentiation accuracy of 85.2% using foot measurements and 82.2% with footprint measurements within the Turkish population (Atamturk 2010). Hemy et al. (2013) demonstrated that footprints from the Western Australian population could achieve a correlation over 0.70 with stature, providing estimation errors of 4.846 cm for males and 4.709 cm for females through multiple regression equations (Hemy et al. 2013). Krishan (2008) achieved excellent results in stature estimation among male Gujjars of India using measurements from footprints and foot outlines, with mean errors of 2.12 cm and 2.17 cm, respectively (Krishan 2008). Awais et al. (2018) employed machine learning algorithms in analyzing footprints, reaching an 87.8% accuracy rate in sex differentiation (Awais et al. 2018). Studies utilizing footprint measurements generally do not differ significantly in terms of accuracy, error margins, and correlation values compared to those employing actual foot measurements, suggesting that real foot and footprint measurements should be assessed using different methods due to the numerous dynamic and static factors affecting footprint measurements, which are typically smaller than the actual foot measurements (Atamturk 2010; Hemy et al. 2013).

In our study, the mean values of Left Foot Height (LFH), Right Foot Length (RFL), and Left Foot Breadth (LFB) were found to be higher in both sexes. However, statistical significance was observed in the dominance of LFH in males and RFL in females. Literature on the subject does not provide a definitive conclusion regarding dominance in right and left foot measurements. Studies have reported separate dominances in right and left foot dimensions among both men and women (Ozden et al. 2005; Zeybek et al. 2008; Sen et al. 2011; Singh et al. 2019).

In a study conducted in Turkey by Özaslan et al. (2003), it was found that using foot height and length in a linear model for stature estimation resulted in R^2 values of 0.49 for males with a standard error of estimate of 4.7 cm, and 0.30 for females with a standard error of estimate of 5.4 cm (Özaslan et al. 2003). In another study, Özaslan et al. (2012) obtained similar results using foot measurements in a multiple linear regression model (Ozaslan et al. 2012). Atamtürk (2010) carried out sex prediction using foot, footprint, and shoe measurements, achieving 85.2% accuracy with linear methods (Atamturk 2010). Considering that the results of our study have been tenfold cross-validated, the observed differences in prediction error and correlation percentages can be attributed to environmental factors influencing growth such as nutrition, physical activities, and climatic conditions, as well as the elapsed time between the studies and the ethnic and regional differences of the populations studied (Nor et al. 2013; Abu Bakar et al. 2017). In contrast to previous studies in Turkey that were conducted in the western and cosmopolitan cities (İstanbul, Ankara, İzmir), our study included individuals primarily from Malatya and its surrounding region in the east.

Linear Discriminant Analysis and Linear Regression methods are traditionally preferred for classification and regression processes, but ANNs show better success in identifying relationships between parameters (Blackard and Dean 1999; Byra 2018). In terms of prediction accuracy, Linear methods fall behind ANNs. While incomplete, erroneous, or unusually variable data pose disadvantages for Linear Discriminant and Linear Regression Analysis, such data enhance variation and offer advantages for ANNs. Linear Discriminant and Regression Analysis techniques require certain preconditions such as linear relationships and normal distributions; ANNs are considered superior in providing non-linear solutions (Kumar and Bhattacharya 2006; Thurzo et al. 2021). In the literature, studies comparing Linear methods and ANNs in sex differentiation on foot bones have shown that models using metatarsal bones along with distal and proximal phalanges can determine sex with 86–98% accuracy (Smith 1997). Senol et al. (2023) achieved 81% accuracy using Linear Discriminant Analysis with 1st and 5th metatarsal and phalanx measurements and increased this to 85% using Decision Tree Algorithm (Senol et al. 2023). In another study, similar measurement methods achieved 95% accuracy using ANNs (Turan et al. 2019). Farhadian et al. (2019) estimated age with a 10.2-year error using Linear Regression from canine teeth and reduced this error to 4.4 years with Neural Networks (Farhadian et al. 2019).

Artificial Neural Networks, generally achieving higher accuracies than linear methods, are a promising approach in Forensic Anthropology (Etli et al. 2019). While Artificial Neural Networks (ANNs) in our study showed higher accuracy in sex prediction (96.3%-97.8%) and stature estimation (4.15 cm-4.07 cm RMSE) compared to Linear Analyses, it's important to acknowledge the contrasting aspects of interpretability between these two methods. Linear models offer clearer interpretability as each weight directly correlates to the influence of a predictor, allowing for more straightforward understanding of how each feature impacts the model (Molnar 2020). This transparency is particularly valuable in forensic contexts where explaining the basis of predictions is crucial. On the other hand, ANNs, despite their superior predictive capability, are less interpretable due to their complex structure involving multiple layers and non-linear transformations. The 'black box' nature of ANNs makes it challenging to discern the specific role and interaction of individual predictors within the model (Zhang et al. 2018). To address interpretability challenges and enhance practical utility, a detailed description of the ANN model, including its architecture and weights, is provided in our manuscript (Supplement 1, 2, 3, 4, 5 and 6 and Tables 8, 9, 10, 11, 12, 13), facilitating replication and application in forensic science.

Our study provides important insights into sex and stature estimation using foot anthropometry within the Eastern Turkish population, primarily represented by university students. However, its focus on a relatively homogenous group in terms of educational background and a specific age range may limit the generalizability of our findings, as it might not reflect the full diversity and lifestyle variations present across the broader Eastern Turkish population.

Conclusions

Sex determination from foot measurements using linear methods achieved around 94% accuracy, and over 97% accuracy when using ANNs. Additionally, stature estimation errors were reduced from 4.15 cm with linear methods to 4.07 cm with ANNs. Our findings indicate that ANNs can work more effectively with such data. We recommend conducting more extensive studies in the future on a larger population, incorporating different parameters, to adequately represent the entire Turkish population.

Abbreviations

SPSS	Statistical package for the social sciences
TEM	Technical error of measurement
rTEM	Relative technical error of measurement
R	Reliability coefficient
RFH	Right Foot Stature
RFL	Right foot length
RFB	Right Foot Breadth
LFH	Left foot stature
LFL	Left foot length
LFB	Left foot breadth
ANNs	Artificial neural networks
MAE	Mean absolute error
RMSE	Root mean squared error
S.D.	Standard deviation

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41935-024-00391-4.

Supplementary Material 1.

Supplementary Material 2.

Supplementary Material 3.

Supplementary Material 4.

Supplementary Material 5.

Supplementary Material 6.

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None.

Authors' contributions

MEP: sample collection, data analysis, writing. BBÖ: sample collection. MO: data analysis, writing. OC: conception, design, critical review.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Inönü University Medical Faculty's Deanship Ethics Board for Non-Interventional Clinical Research approved the study's ethical protocol under the approval number 2022/3058, dated February 8, 2022. This research was conducted in accordance with the principles of the Helsinki Declaration. Informed written consent was obtained from participants prior to data collection.

Consent for publication

All participants provided their written consent for publication, with the explicit understanding that no personal identifiers, images, or videos would be disclosed. The study utilizes their anonymized data, including measurements such as height, weight, and lower extremity measurements, thus ensuring the absence of personally identifiable information in the published data.

Competing interests

The authors declare that they have no competing interests.

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