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Original Article

Forensic Section

A Cross-sectional Study on Stature Estimation from Arm Lengths among North Indian Population using Machine Learning

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ABSTRACT

Introduction: During forensic investigations, cases are often encountered where the deceased bodies are in a partially or completely decomposed, charred, or skeletonised condition. In such scenarios, the examination of skeletal remains becomes imperative to establish the identity of an individual. Anthropometric measurements assist in identifying these parameters with accuracy.

Aim: To assess the relationship between upper limb dimensions and stature in North Indian adults using regression formulae and a decision forest-based model for stature estimation from these dimensions.

Materials and Methods: A cross-sectional study was conducted among 262 (M=120/F=142) students aged between 18 and 25 years using random sampling. This study was carried out in the Department of Forensic Science, Faculty of Applied and Basic Sciences, SGT University, Gurugram, Haryana, India from October 2023 to January 2024. The primary inclusion criteria stipulated that participants should be of North Indian origin (New Delhi NCR, Haryana and Punjab regions) and should not have suffered from any congenital or traumatic deformities of the upper and lower limbs. The stature, forearm length and Total Arm Length (TAL) were measured based on anthropometric points. Descriptive statistics, p-values, t-values and Pearson's correlation coefficient were studied using Statistical Package of Social Sciences (SPSS) software version 21.0 and a decision forest model was designed on a cloud-based coding platform using Python programming language.

Results: The present study depicts a higher mean value of TAL (55.9±4.18) and stature (175.41±5.63) for males in comparison to females. All the measurements were statistically significant, with p-values <0.001. It also reveals a strong positive correlation between TAL and stature for both males (r-value=0.951) and females (r-value=0.975). The decision forest model achieved an accuracy of 0.951 and a Root Mean Square Error (RMSE) of 1.75.

Conclusion: The present study suggests that stature shows strong correlations with forearm length and TAL for both sexes. The decision forest model can classify the sexes with an accuracy of 77.5% using TAL. However, demographic variations must be considered when applying the regression formulae. Additionally, such anthropometric data should be updated regularly due to secular and temporal changes within the population.

Keywords: Decision forest, Forensic anthropology, Regression analysis

INTRODUCTION

Personal identification of unknown deceased individuals is one of the most important steps in criminal investigations. In cases of highly decomposed bodies, charred or dismembered remains, skeletal evidence serves as the best tool for identification. Stature is one of the most important variables in establishing the biological profile from such skeletal evidence, as it exhibits ethnic and population variations [1]. Stature estimation also plays a significant role in osteoarchaeological studies to determine sexual dimorphism and secular variations. It is affected by various genetic and epigenetic factors, namely nutrition, sex, age, physical activity and environmental conditions [2].

Stature estimation can be conducted using two methods: the anatomical method, which usually requires the entire skeleton and the mathematical method, which utilises several regression formulae. The initial research was conducted in 1888 by Rollet E, who used measurements from 50 male and 50 female deceased individuals to depict the relationship between different body measurements and stature [3]. It is primarily based on the principle that an individual's height has a definite and linear relationship with various human bones and body parts [4].

Furthermore, different studies conducted on South African, North Indian and Central Indian populations have revealed a strong positive correlation between stature and various long bone measurements. Several linear regression models have also been developed for these populations [4-6]. Krishan K and Sharma A conducted a study on the North Indian Rajputs belonging to Himachal Pradesh to estimate stature from hand and foot dimensions using linear regression, obtaining a strong positive correlation [7]. Shakya T et al., and Nandi ME et al., also conducted similar studies on the Nepalese and Nigerian populations, where the "r" values were 0.895 and 0.72 for the correlation between stature and arm length, respectively [8,9].

However, all these studies unanimously concluded that regression equations and correlation coefficients are population-specific. Therefore, these measurements need to be developed specifically for different populations and updated regularly due to secular and temporal changes [10].

With the advent of technology, machine learning algorithms are increasingly being used in forensic anthropological studies. Stature estimation can be established using various tools, such as linear regression, decision trees, random forests and neural networks [11]. Machine learning algorithms require relevant input features to produce reliable predictions. Various skeletal measurements, such as long bone lengths (femur, tibia, humerus, radius), vertebral column measurements and skull dimensions, are used to estimate stature. Czibula G et al., have suggested the use of two supervised regression models based on Artificial Neural Networks (ANN) and Genetic Algorithms (GA) to determine stature from the lower and upper limb bone measurements of the Terry postcranial osteometric database, where both machine learning algorithms performed well with low overall error values (3.1 for ANN and 3.18 for GA) [12]. A dataset of known statures and skeletal measurements is required to train a machine learning algorithm. The choice of algorithm depends on the specific requirements and characteristics of the dataset. Once trained, the model must be tested to determine its accuracy and efficiency. The evaluation of the model is accomplished by utilising a separate validation dataset that was not used during the training phase. Once the evaluation is confirmed, the model can be used to estimate the size of unknown skeletal remains [13,14].

Decision forests, also known as random forests, are an ensemble machine learning method. They are particularly useful for the classification of sex based on skeletal measurements and for predicting regression. A decision forest is a collection of decision trees, each of which makes predictions individually and the final forecast is generated by aggregating the predictions of all the trees [11]. The rationale behind using a decision forest-based approach can be attributed to the fact that other neural networks require the segregation of samples into anthropometric or somatometric (numerical) and somatoscopic (categorical) segments, whereas a decision forest has built-in features to identify different types of input data [11]. Random forests have several advantages for stature estimation, including their ability to handle complex relationships between features such as age, weight, sex, ethnicity, fragmentation and congenital or traumatic deformities of bones, along with the target variable (stature). They are resistant to overfitting and can provide feature importance rankings.

Decision forest models are relatively easier to interpret due to their individual tree structure, whereas other machine learning algorithms, such as Support Vector Machines (SVM) and ANN, are difficult to interpret due to complex hyperplane boundaries and hidden layers, respectively. Missing values due to malfunctioning sensing systems are one of the most frequently occurring issues in data analysis and SVMs and ANNs require imputation or pre-processing of data; however, decision forests do not require such pre-processing. Nonetheless, it is crucial to ensure that the training data is representative and covers a diverse range of individuals to obtain accurate and reliable stature estimations [15,16].

Statistical tools and ML-based prediction models are also used to generate formulas that assist in identifying indigenous population groups. Often, during forensic investigations, the presence of commingled populations and partial skeletal remains poses a challenge to using traditional formulas [17]. There is currently a deficiency in machine learning anthropometric databases concerning stature estimation and its correlation to limb length within the Indian population. The present paper, therefore, aimed to study the correlation, devise regression formulae and classify sex from stature using a decision forest-based model, specifically for the adult North Indian population.

MATERIALS AND METHODS

A cross-sectional study was conducted on 262 healthy adults (M=120/F=142) aged between 18 and 25 years at the Department of Forensic Science, SGT University, Gurugram, Haryana, India. Gurugram is one of the fastest-developing cities in the country, with its large corporate sectors and educational hubs housing a significant number of young people. The participants were selected using a random sampling method and informed consent was obtained following the approval of the Institutional Ethical Committee (Ref No: SGTU/FOSC/2023/1481) in both English and Hindi. The study was conducted from October 2023 to January 2024, with measurements taken between 9:00 a.m. and 11:00 a.m. to avoid diurnal changes [5]. The study was time-bound and all participants available during this period were included.

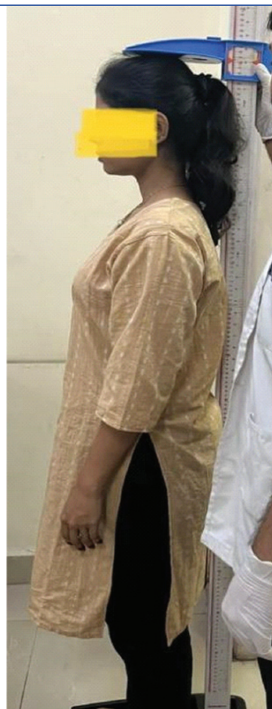
Inclusion and Exclusion criteria: The inclusion criteria were as follows: a) participants belonged to North Indian origin, specifically from the states of New Delhi, Punjab and Haryana and were young adults aged between 18 and 25 years; b) participants were volunteers who provided their consent. The exclusion criteria included: a) any individual with dwarfism or congenital or traumatic abnormalities affecting stature or upper limbs; b) any individual who had undergone reconstructive surgeries that might alter their stature or upper limb dimensions.

Study Procedure

Participants were instructed to stand with their backs towards the wall and their heads positioned in the Frankfurt Horizontal Plane. The forearm and TAL were measured using a measuring tape [Table/Fig-1], while stature was measured using a stadiometer [Table/Fig-2]. The measurements were taken with the utmost precision and reliability. To ensure the reliability of the data, all observations were recorded by a single observer. The measurements taken were as follows:

1. **Stature (S):** This denotes the distance from the base to the vertex.
2. **Total Arm Length (TAL):** This is measured from the tip of the humerus (acromion) to the tip of the middle finger (dactylion).
3. **Forearm Length (FL):** This is measured from the palmar end of the pisiform bone to the medial epicondyle of the humerus.

[Table/Fig-1]: Total Arm Length (TAL) and forearm length measured using a measuring tape.



[Table/Fig-2]: Stature measurement using stadiometer.

Decision forest approach: The authors aimed to predict stature and sex using the same dataset. A decision forest model was chosen as it is a supervised learning technique capable of performing both regression and classification. To train the model, the dataset was stored as a Comma Separated Value (CSV) file and a pandas DataFrame was used to load the data. No pre-processing of the data was required, as the entire dataset, comprising stature, forearm length and TAL, consisted of numerical values.

After loading the data, it was split into two parts: the training dataset and the testing dataset. Out of the 262 samples, 210 were used for training and the remaining 52 (M=32/F=20) were used for testing. The data was split in an 80:20 ratio to optimise the model and reduce variance in both the performance statistics and parameter estimates. The only additional parameter used in the decision forest was "max-depth," which was set to "5" to prevent overfitting [11].

Once the data was split, it was converted from the pandas DataFrame into a TensorFlow DataFrame. The model was then evaluated using the testing samples. In the final step, the model was plotted to observe the root node and decision nodes. All the data was compiled in Google Colab (https://colab.research.google.com/github/tensorflow/decisionforests/blob/main/documentation/tutorials/beginner_colab.ipynb), a cloud-based platform that allows users to code using the Python programming language.

STATISTICAL ANALYSIS

Descriptive statistics were statistically analysed using SPSS version 21.0. and p-values, t-values, Sexual Dimorphism Index (SDI) and Pearson's correlation coefficient "r" were calculated. Regression equations for stature estimation were generated for both males and females using TAL and forearm length.

RESULTS

The descriptive statistics, including mean values, standard deviation, t-value, p-value and Sexual Dimorphism Index (SDI) is depicted in [Table/Fig-3]. The formula used for calculating SDI is: (Mean of Male/ Mean of Female - 1) * 100 [5].

Variables (cm)	Males (n=120)	Females (n=142)	t-value	p-value	SDI
S	175.41±5.63	156.79±5.87	8.12	<0.001	11.87
FL	30.06±1.4	26.19±1.3	6.26	<0.001	14.77
TAL	55.9±4.18	48.67±2.62	4.30	<0.001	14.85

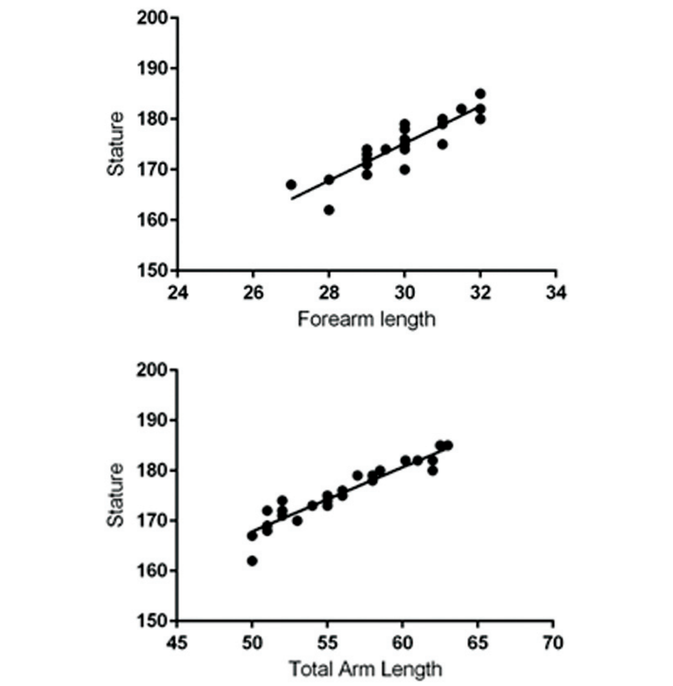
[Table/Fig-3]: Descriptive statistics, p-value, t-value and Sexual Dimorphism Index (SDI) (N=262).

All the measurements showed significant sexual dimorphism (p<0.001). The Pearson's correlation coefficient of forearm length and TAL with stature is 0.917 and 0.951, respectively, in males. The results depict a strong positive correlation of stature with TAL and forearm length for both males and females. The scatterplots of stature with forearm length and TAL for both sexes have also been demonstrated [Table/Fig-4,5].

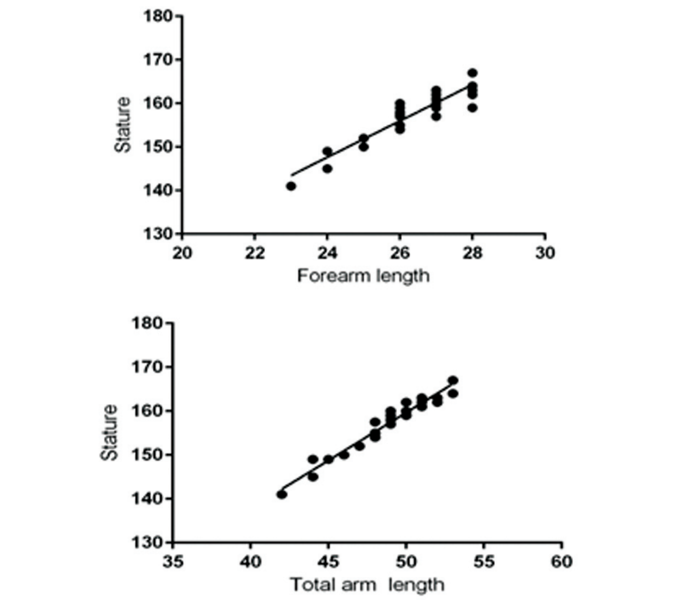
The Standard Error in Estimation (SEE) of stature from the generated regression equations is low, thereby revealing high reliability [Table/Fig-6].

The decision forest model depicted cut-off values for the classification of sexes and the highest sexing accuracy [Table/Fig-7]. The results of the decision forest were based on the testing data of 52 samples (M=32, F=20). The sample decision tree provided two types of nodes, namely, the root node and the decision node. The node at the top depicts the root node, while those below it depict the decision nodes. The red-coloured nodes indicate a higher percentage of correctly identified samples in the population, whereas the blue nodes depict a lower percentage [Table/Fig-8] [18].

The highest sexing accuracy was depicted by TAL (77.5%), followed by stature (72.5%) and forearm length (57.5%). The order of ranking of features according to their sexing accuracy is imperative in



[Table/Fig-4]: Scatterplots of stature with forearm length (27-32 cm) and Total Arm Length (TAL) (50-63 cm) for males.



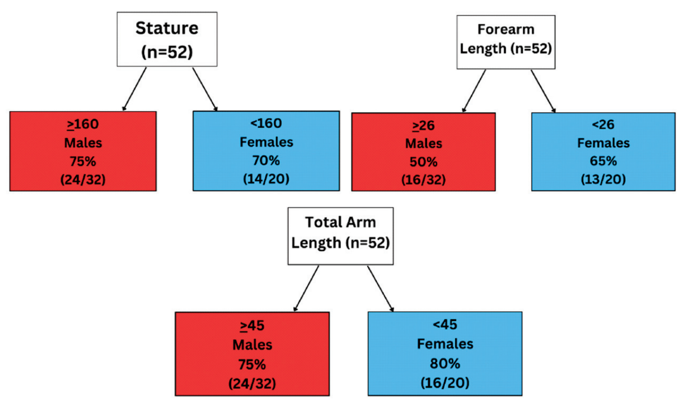
[Table/Fig-5]: Scatterplot of stature with forearm length (23-28 mm) and Total Arm Length (TAL) (42-53 mm) for females.

Sample	Regression equations	r-value	p-value	Actual stature	Calculated stature	SEE
Males	S=3.674 FL+64.945	0.917	<0.001	175.41	175.27	0.14
	S=1.279 TAL+103.861	0.951	<0.001	175.41	175.35	0.06
Females	S=4.175 FL+47.428	0.924	<0.001	156.79	156.77	0.02
	S=2.183 TAL+50.523	0.975	<0.001	156.79	156.76	0.03

[Table/Fig-6]: Simple linear regression equations, Pearson's Correlation co-efficient and Standard Error Estimation (SEE) for both the sexes.
[2]"Simple Linear Regression and correlation "tests were performed using SPSS software V.21.00

Variables (cm)	Cut-off values	Sexing accuracy		
		Males % (n=32)	Females % (n=20)	Overall % (n=52)
S	♂≥160<♀	75	70	72.5
FL	♂≥26<♀	50	65	57.5
TAL	♂≥45<♀	75	80	77.5

[Table/Fig-7]: Cut-off values generated by decision trees and sexing accuracy for both males and females.
[3]Decision Forests created in Google-Colab Tensor Flow



[Table/Fig-8]: Decision forest depicting cut-off points and sexing accuracy based on stature, forearm length and Total Arm Length (TAL).

establishing the importance of TAL in stature estimation. The model also generated an out-of-bag evaluation accuracy of 0.951. The Root Mean Square Error (RMSE) value obtained using the decision forest-regression model is 1.75.

The formula for estimating stature from forearm length and TAL is:

Stature (y)=Slope*Independent variable (x)+Constant [5]

DISCUSSION

In medicolegal examinations of mass disasters, charred, decomposed and dismembered body parts, forensic anthropolo-gists can assist in personal identification from skeletal remains. Stature, sex, age and ethnicity estimation are the "Big Four" of personal identification. The present study shows statistically significant ($p<0.001$) differences in stature, forearm length and TAL among North Indian male and female subjects. Linear regression equations, as well as multiplication factors for stature estimation from TAL and forearm length, were also devised for both sexes.

The age group (18-25 years) chosen for the present study was selected to ensure that complete growth and development of stature had occurred. Additionally, age-related diseases affecting the bones and joints could be avoided. Studies conducted within the Amritsar population depicted an "r" value of 0.660 between stature and upper arm length for males [19], whereas a cross-sectional study on healthy individuals aged between 18-25 years from the Telangana population demonstrated a strong correlation between stature and forearm length, with an r^2 of 0.73 [20]. The present study also reveals that forearm length and TAL have a strong correlation with stature for both males (r=0.95) and females (r=0.97). A similar observation has been reported by Arif M et al., and Ebrahimi B et al., [21,22].

Different studies conducted on Bengali (r=0.82), Karnataka (r=0.816), Iranian (r=0.643), Sudanese (r=0.725) and Egyptian (r=0.89) adults aged between 18-30 years demonstrated a strong positive correlation between arm length and stature, which is consistent with the results of the present study [23-27]. The variation in findings across different population groups may be the result of varying genetic backgrounds, nutrition, climate, physical activity and the number of samples included in each study.

Stature estimation from phalanges and hand dimensions has also been conducted among Korean (r=0.603), North Indian (r=0.673) and South Indian (r=0.752) populations, which revealed a strong correlation with stature [28,29]. In the present study, simple linear regression equations were also derived from forearm length and TAL. The mean error for the measurement of stature using these equations varied from ±0.02 to ±0.14 for both males and females. This was comparatively lower than the SEE values reported in the Turkish (±3.49), Sudanese (±3.54 to ±5.85) and Iranian (±6.03 to ±6.9) populations [26,30,31]. However, step-wise multiple linear regression can also be performed by combining forearm length and TAL for stature estimation.

Since artificial intelligence and machine learning are being rapidly employed in the field of forensic anthropology, we aimed to create a prediction model using a decision forest algorithm to obtain classifications of sex and regression for stature estimation. Unlike neural networks, which require sample processing to differentiate between categorical and numerical data, decision forests perform this task natively and do not require such processing. The Mean Square Error (MSE) and RMSE were 3.065 and 1.75, respectively. The MSE helps to estimate the error in a prediction model. Under ideal conditions, the value of MSE should be 0, but achieving this in practice is challenging.

In a study by Son Y and Kim W, an attempt was made to compare different machine learning algorithms while estimating stature from anthropometric data. The results indicated that SVMs achieved a higher estimation accuracy of 0.756 [32]. However, the present study shows an accuracy of 0.951 when estimating stature from upper limb length. The decision forest model has generated cut-off points for stature (160 cm), forearm length (26 cm) and TAL (45 cm). These cut-off points assisted in the classification of sexes, as individuals below these points were identified as females, while those above were identified as males. A classification accuracy was also calculated and TAL provided the highest accuracy of 77.5%. Stature and forearm length followed next in terms of higher sexing accuracy. A greater sexual dimorphism in TAL among males may be associated with the development of muscles, functionality and fat deposition [32].

The use of a homogeneous sample can lead to potential biases, making the results less applicable to the entire population. To mitigate this, random stratified sampling may be employed to ensure that the sample is representative of the target population. The present study finds its significance in clinical, forensic and archaeological perspectives. Stature can vary with age, ethnicity and sex, thereby serving as a reliable parameter in creating a biological profile. Such profiles are imperative for personal identification, diagnostic purposes and reconstructive surgeries. Population-specific data, especially for young adults, is scarce and this decision forest approach represents a novel attempt within the North Indian population.

Machine learning algorithms require larger training datasets to function efficiently and their complex interpretation necessitates skilled personnel. It would be beneficial for forensic anthropologists to conduct further research in different populations and age groups to assess the performance of each machine learning algorithm.

Limitation(s)

The final sample size was smaller than desired, despite efforts to increase it. North Indian adults would require a larger sample size, with adequate geographical and social heterogeneity, for more reliable results. The regression equations are specific to the North Indian population and should not be used for other populations. The models developed in the present study were based on adult samples and are not applicable to juveniles.

CONCLUSION(S)

The present study demonstrates a strong relationship between stature and arm lengths. All the equations developed have provided reliable stature estimation, exhibiting a strong positive correlation and low error of estimation. In cases involving mutilated, dismembered remains and mass disasters, such anthropological databases can be helpful in personal identification. However, it is essential to utilise diverse population data to validate the model's applicability. These results can also be applied in reconstructive orthopaedic surgery and paleoanthropological studies.

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