Original Article

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Performance of the Machine Learning Algorithm in Stature Estimation Using Scapula Measurements from Post-Mortem Computed Tomography in a Thai Male Population

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Abstract:

Objective: This study attempted to investigate the performance of stature prediction models from scapular dimensions based on post-mortem computed tomography (PMCT) using machine learning algorithms within the male population of Southern Thailand.

Material and Methods: Linear Regression (LR), K-Nearest Neighbors (KNN), Random Forest tree (RF), and Support vector machine (SVM) algorithms were used to create the stature estimation model. Then its performance was compared by coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

Results: Machine learning is a valuable tool for estimating stature within this demographic. LR algorithm provided the best performance matrices, with the highest R^2 being 0.316, and the lowest values for MAE, MSE, and RMSE being 4.379 cm, 29.530 cm, and 5.382 cm, respectively.

Conclusion: The machine learning algorithm demonstrated valuable tools for estimation stature. However, it is essential to note that complex machine learning models do not always produce better performance measures than non-complex models.

Keywords: machine learning, post-mortem computed tomography, stature estimation, scapular measurement, southern Thai population

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Introduction

Stature is a crucial aspect of the biological profile, which includes gender, age, stature, and ancestry. It is a valuable tool for identifying unknown individuals, especially when their height differs from the average height of their population' by assisting in narrowing down the number of possible missing persons before definite identification[1]. Estimating stature from skeletal remains can be categorized into anatomical and mathematical methods. The anatomical method involves calculating stature by adding up the lengths of the bones that contribute to overall body height. Conversely, the mathematical method calculates stature based on the length of one or more individual bones[2]. Although the anatomical approach is more accurate in estimating stature than the mathematical method the full skeletal remains are required to estimate stature[3]. Due to the constraints of the anatomical approach, the mathematical method, may be better suited for forensic cases wherein the entire skeletal remains are typically not found.

Previous studies have determined that the most precise approach to estimating stature involves measuring long bones[4,5]. However, there are situations where it is not possible to recover long bones due to various factors, such as limited damage, fragmentation, animal scavenging, dispersion, burn incidents, disasters, dismemberment, and so forth[6–8]. In such situations, it may be necessary to use alternative skeletal components other than long bones, such as the skull[9,10], pelvis[8], vertebrae[11–14], sternum[15], scapula[6,7,16,17], clavicle[18] and bones of the hand and foot[19–23].

The scapula is an osseous structure characterized by its unique morphology and considerable dimensions, rendering it conspicuous when encountering a cadaver[24]. Prior research has demonstrated a relationship between the size of the scapula and a person's height. This correlation allows for the development of regression equations that can be used to estimate stature. These findings have been supported by studies conducted in Italian, Japanese, and Chinese population[6,7,16,17]. In addition, Zhang et al.[17]'s work suggests that multiple measurement methodologies are available for estimating stature from a partial scapula.

Linear regression is a widely used statistical technique for creating models to estimate height. Machine learning is an area of research focusing on developing models that can improve their performance by learning from data and acquiring domain-specific knowledge[25]. Previous studies have shown that machine learning surpasses the conventional approach in accurately estimating stature. In their study, Czibula et al.[26] examined the use of machine learning methods, particularly artificial neural networks and genetic algorithms, to estimate the height of individuals based on archaeological bone remains. The findings demonstrated that artificial neural networks (ANN) and genetic algorithms effectively estimate stature from archaeological skeleton remains. Furthermore, Parlak et al.[27] reported that ANNs achieve lower stature estimation inaccuracies (4.07 cm vs. 4.15 cm) than linear approaches in Eastern Turkish.

There has been a significant rise in the use of post-mortem computed tomography (PMCT) due to its ability to be performed quickly and without invasive procedures, such as bone preparation or dissection[8,11,13,16]. Moreover, it provides a substantial quantity of information compared to conventional radiography[16]. Therefore, PMCT has become a promising tool in forensic anthropology, with considerable potential for future methodological developments.

To the best of our knowledge, there is currently no extensive research on utilizing machine learning algorithms to estimate stature based on the scapula. Furthermore, the transferability of study findings from one population to another may be limited by the influence of genetic and environmental factors on bone formation[7,28]. Therefore, this study attempted to develop a stature prediction model using various machine learning algorithms from PMCT based on scapular dimensions in the male population of Southern Thailand.

Material and Methods

The ethical committees at our university approved this study, with the necessity of obtaining informed permission from each person being exempted. The sample size, calculated using the GPower version 3.1.9.7 application, based on the prior study by Zhang et al.[17], was a minimum of 75 male samples. The data were obtained from 150 male deceased having undergone PMCT and autopsy at the Forensic Medicine and Toxicology Unit, Department of Pathology, Faculty of Medicine, Prince of Songkla University, between January 2021 and December 2022. The inclusion criteria of the sample consisted of Thai nationals aged 25 years or older living in the South of Thailand. This age group was chosen to ensure the complete development of the scapula[29]. The age, gender, and stature of the individuals were identified and documented. Participants with scapula-related conditions, such as fractures, burns, cancer, congenital deformities, decomposing artifacts and others, were not included in the study.

The stature of the deceased body was determined by measuring the distance from the top of the head to the bottom of the foot while lying flat and after the stiffness of the body after death had subsided[30]. The adjusted stature was calculated by subtracting 2.0 cm from the measured stature to account for post-mortem alterations, such as reduced spinal curvature[4,30].

Whole-body imaging was performed utilizing Aquilion Lightning™, a 16-row, 32-slice helical computed tomography (CT) system developed by Canon Medical Systems for PMCT. The scanning protocol consisted of the following parameters: a collimation of 1 mm, a reconstruction interval of 1 mm, a tube voltage of 120 kV, a tube current of 50 mAs, and a rotation time of 0.75/s. The picture data were analyzed using Vitrea® V.6.9.0 software to create three-dimensional reconstructed images. Afterward, the right scapula was manually removed from these pictures to take additional measurements.

The scapulars were measured with a precision of up to 0.1 mm. The standards for measuring the scapula were developed as follows:

Morphological breadth (MB): the distance between the medial margin and the middle of the glenoid cavity[17].

Morphological length (ML): the distance between the end of the inferior angle and the vertex of the superior angle[17].

Longitudinal scapular length (LSL): the distance between the end of the inferior angle and the superior margin of the coracoid process[7,16,17].

Longitudinal maximum length (LML): the distance between the end of the inferior angle and the superior margin of the acromion process[17].

Transverse scapular length (TSL): the distance between the glenoid cavity's medial and inferior margins[7,16,17].

Length of axillary margin (LAM): the distance between the end of the inferior angle and the inferior margin of the glenoid cavity[17].

A third-year forensic resident Thutchai Opaburanakul (TO) conducted the measurements of all samples. Next, a random sample of 15 participants had repeated measurements by a TO and a forensic physician to assess the level of agreement among and between observers. Precision was estimated by calculating the TEM, relative TEM (rTEM), and coefficient of reliability (R^2)[31,32]. The acceptable rTEM values were 1.5% for intraobserver error and 2.0% for interobserver error[31].

Statistics

Descriptive statistics; such as the mean, standard deviation, and range, were used to illustrate the value of each measurement. The Pearson correlation coefficient was employed to compute the correlation between stature and each scapular measurement parameter. Statistical significance was observed when the p-value was below 0.05, and all data were analyzed using Anaconda Python version 3.11.5.

Machine learning

The stature estimation model was constructed using Linear Regression (LR), K-Nearest Neighbors (KNN), Random Forest tree (RF) and Support vector machine (SVM) algorithms based on measurements that showed a substantial correlation with the adjusted stature. The models were constructed utilizing Anaconda Python version 3.11.5, incorporating the scikit-learn package.

Feature selection

The Recursive Feature Elimination with a cross-validation (RFECV) method was employed to choose features, using a cross-validation value of 5. The method utilized linear regression and linear SVM models. The chosen features were used to create the final model for estimating stature.

Model development and matrices performance

The parameters chosen were employed to create models for estimating stature, both with and without hyperparameter adjustment. The hyperparameter tuning was conducted for the ML algorithms; except for LR, using the GridsearchCV methodology, and the range of hyperparameter tuning values is presented in Table 1. The performance metrics of the ML model were evaluated using 10-fold cross-validation, assessing the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

Table 1 The hyperparameter and tuning range of the machine learning

Method	Hyperparameter	Tuning range
K-nearest neighbors	leaf_size	1-50
	n_neighbors	1-30
	p	1, 2
Random forest	n_estimators	5, 10, 20, 30, 40, 50, 100
	max_features	sqrt, log2
	max_depth	5-12
	max_leaf_nodes'	5-12
Support vector machine	C	1-10
	kernel	poly, linear, rbf, sigmoid
	gamma	auto', 0.001, 0.0001, 0.1, 1, 10

p=power parameter for minkowski metric, C=regularization parameter

Results

The rTEM for intraobserver error was less than 1.5% (ranging from 0.1% to 0.2%), and for interobserver error it was less than 2.0% (ranging from 0.7% to 1.1%). The coefficient of reliability (R^2) for all measurements was greater than 0.90 (ranging from 0.92 to 0.99) (Table 2). Table 3 displays the descriptive data for age, adjusted stature, and scapular measurement parameters, including the range, mean, and standard deviation (S.D.). There was a substantial correlation between all scapular measurements and the adjusted stature. LML showed the best correlation with adjusted stature, followed by TSL and MB. On the other hand, LAM showed the lowest correlation with adjusted stature (Table 3 and Figure 1).

The feature selection in our inquiry was performed utilizing the RFECV technique, based on LR and linear SVM algorithms. The LR method selected three scapular measurements: LML, TSL and LAM. On the other hand, the linear SVM chose five specific measurements: ML, LSL, LML, TSL, and LAM. The linear regression model, incorporating LML, TSL and LAM parameters, demonstrated superior performance in estimating stature compared to SVM, KNN and RF in the non-hyperparameter tuning group. The LR model's average R^2 was 0.316, and the lowest values for MAE, MSE, and RMSE were 4.379 cm, 29.530 cm, and 5.382 cm, respectively. The RF model exhibited the poorest performance in the non-hyperparameter tuning group, with an average R^2 of 0.113. In addition, it achieved the lowest MAE of 4.815 cm, MSE of 36.482 cm, and RMSE of 6.004 cm. The details are displayed in Table 4.

Hyperparameter adjustment enhanced the performance metrics of KNN, RF, and SVM. Nevertheless, the performance metrics did not surpass those of LR. The SVM model demonstrated superior performance in estimating stature compared to the hyperparameter-tuned models. The SVM-based stature estimate model, using all parameters, yielded the highest average R^2 value of 0.313, and the model achieved the lowest MSE value of 29.501. However, the SVM model, utilizing LML, TSL, and LAM, indicated the lowest average MAE and RMSE values: 4.292 cm and 5.385 cm, respectively. The stature estimation model utilizing RF with ML, LSL, LML, TSL, and LAM showed the poorest performance among the hyperparameter-tunned models. The average was 0.216, and the lowest MAE, MSE, and RMSE were 4.668 cm, 32.558 cm, and 5.729 cm, respectively. The information is presented in Table 5.

Table 2 Technical error of measurements, relative technical error of measurements, and coefficient of reliability (n=15)

Measurement	Intraobserver			Interobserver		
	TEM	rTEM	R	TEM	rTEM	R
MB	0.17	0.15	0.99	1.09	1.01	0.94
ML	0.12	0.08	0.99	1.50	0.98	0.97
LSL	0.19	0.11	0.99	1.93	1.12	0.96
LML	0.19	0.10	0.99	1.38	0.72	0.98
TSL	0.25	0.22	0.99	1.14	1.02	0.92
LAM	0.27	0.20	0.99	1.21	0.90	0.98

TEM=technical error of measurement, rTEM=relative technical error of measurement, R=coefficient of reliability, MB=morphological breadth, ML=morphological length, LSL=longitudinal scapular length, LML=longitudinal maximum length, TSL=transverse scapular length, LAM=length of axillary margin

Table 3 Descriptive statistics of age, adjusted stature, scapular measurement parameters, and the correlation of scapular measurements with adjusted stature

	Subjects (n=150)		Correlation coefficient	p-value
	Range	Mean (S.D.)		
Age (years)	25.00-90.00	49.10 (15.96)		
Adjusted stature (cm)	148.00-183.00	166.59 (6.84)		
MB (mm)	93.50-117.20	106.05 (5.13)	0.52	<0.01
ML (mm)	136.60-176.10	152.97 (7.55)	0.48	<0.01
LSL (mm)	150.50-199.40	171.85 (7.68)	0.50	<0.01
LML (mm)	170.30-214.50	190.12 (7.95)	0.57	<0.01
TSL (mm)	98.50-120.70	110.41 (4.93)	0.54	<0.01
LAM (mm)	117.10-149.40	131.45 (7.12)	0.45	<0.01

S.D.=standard deviation, MB=morphological breadth, ML=morphological length, LSL=longitudinal scapular length, LML=longitudinal maximum length, TSL=transverse scapular length, LAM=length of axillary margin, cm=centimeter, mm=millimeter

Table 4 The performance metrics stature estimation model without hyperparameter tuning

Method	R^2 (S.D.)	MAE (S.D.) cm	MSE (S.D.) cm	RMSE (S.D.) cm
All parameter				
LR	0.288 (0.148)	4.436 (0.702)	30.801 (8.302)	5.502 (0.728)
KNN	0.154 (0.278)	4.727 (0.840)	35.670 (10.640)	5.909 (0.868)
RF	0.124 (0.253)	4.855 (0.643)	36.572 (8.065)	5.993 (0.663)
SVM	0.196 (0.183)	4.694 (0.723)	34.678 (8.965)	5.841 (0.751)
LR-based (LML, TSL, LAM)				
LR	0.316 (0.167)	4.379 (0.708)	29.530 (8.396)	5.382 (0.748)
KNN	0.153 (0.346)	4.852 (0.885)	35.481 (11.542)	5.885 (0.921)
RF	0.113 (0.258)	4.815 (0.476)	36.482 (8.056)	6.004 (0.620)
SVM	0.231 (0.194)	4.614 (0.712)	33.314 (10.029)	5.713 (0.819)

Table 4 (continued)

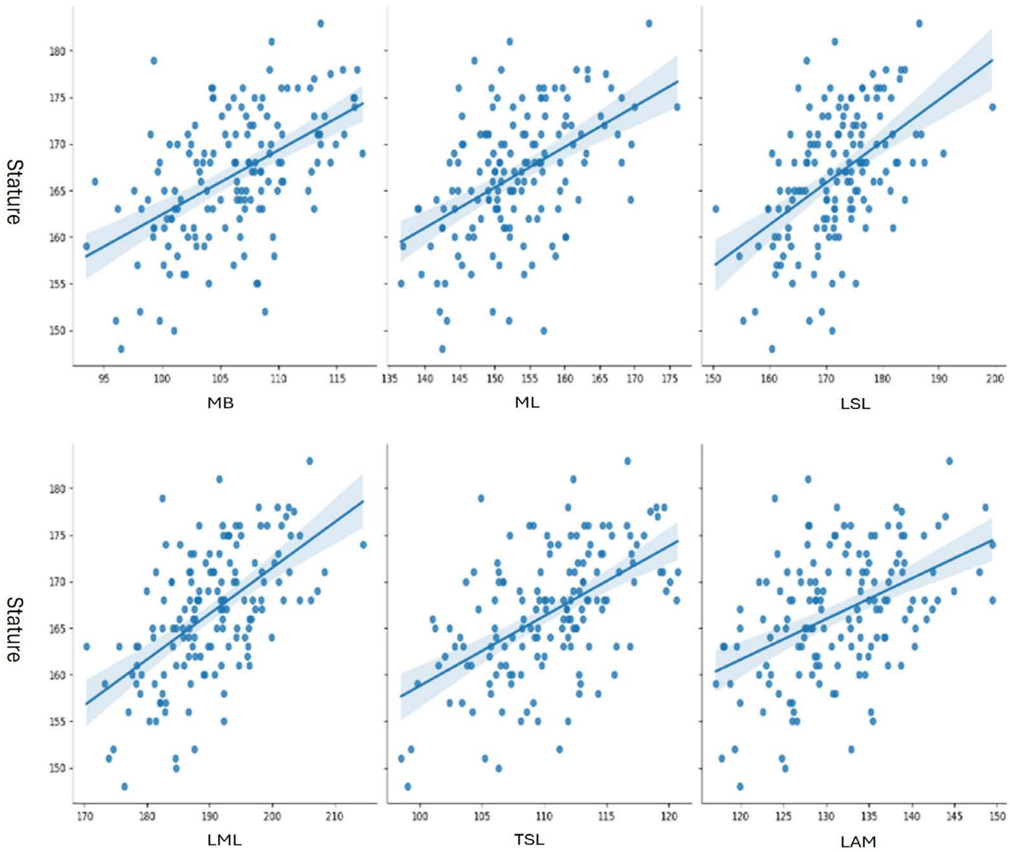
Method	R^2 (S.D.)	MAE (S.D.) cm	MSE (S.D.) cm	RMSE (S.D.) cm
SVM-based				
(ML, LSL, LML, TSL, LAM)				
LR	0.300 (0.154)	4.386 (0.700)	30.258 (8.334)	5.451 (0.740)
KNN	0.140 (0.242)	4.847 (0.766)	36.266 (8.422)	5.980 (0.709)
RF	0.140 (0.258)	4.816 (0.705)	36.732 (8.660)	6.042 (0.682)
SVM	0.202 (0.186)	4.645 (0.732)	34.477 (9.142)	5.821 (0.771)

KNN=K-nearest neighbors, RF=Random Forest tree, SVM=Support vector machine, ML=morphological length, LSL=longitudinal scapular length, LML=longitudinal maximum length, TSL=transverse scapular length, LAM=length of axillary margin, MAE=mean absolute error, MSE=mean squared error, RMSE=root mean squared error, S.D.=standard deviation, cm=centimeter, LR-based=linear-regression based

Table 5 The performance metrics of the stature estimation model with hyperparameter tuning

Method	R^2 (S.D.)	MAE (S.D.) cm	MSE (S.D.) cm	RMSE (S.D.) cm
All parameter				
KNN	0.252 (0.182)	4.523 (0.549)	31.954 (7.227)	5.617 (0.637)
RF	0.229 (0.253)	4.750 (0.388)	33.035 (8.868)	5.849 (0.626)
SVM	0.313 (0.113)	4.414 (0.510)	29.501 (5.757)	5.406 (0.521)
LR-based (LML, TSL, LAM)				
KNN	0.280 (0.232)	4.503 (0.701)	31.094 (9.952)	5.509 (0.862)
RF	0.227 (0.246)	4.666 (0.619)	32.876 (8.302)	5.665 (0.705)
SVM	0.312 (0.187)	4.292 (0.682)	29.510 (8.077)	5.385 (0.715)
SVM-based				
(ML, LSL, LML, TSL, LAM)				
KNN	0.251 (0.152)	4.538 (0.532)	32.037 (6.438)	5.630 (0.582)
RF	0.216 (0.219)	4.668 (0.687)	32.558 (7.346)	5.729 (0.619)
SVM	0.294 (0.135)	4.378 (0.573)	30.210 (6.141)	5.468 (0.559)

KNN=K-Nearest Neighbors, RF=Random Forest tree, SVM=Support Vector Machine, ML=morphological length, LSL=longitudinal scapular length, LML=longitudinal maximum length, TSL=transverse scapular length, LAM=length of axillary margin, LR-based=linear-regression based, MAE=mean absolute error, MSE=mean squared error, RMSE=root mean squared error, S.D.=standard deviation, cm=centimeter



MB=morphological breadth, ML=morphological length, LSL=longitudinal scapular length, LML=longitudinal maximum length, TSL=transverse scapular length, LAM=length of axillary margin

Figure 1 Scatter plots for correlation between stature and scapular measurements

Discussion

This study estimates stature from PMCT images of scapular bones using a machine-learning algorithm in the southern Thai male population. The findings indicated machine learning is a valuable tool for estimating stature within this demographic. The results of this study indicated that the LR algorithm provided the best performance, with the highest R^2 at 0.316, and the lowest values for MAE, MSE, and RMSE were 4.379 cm, 29.530 cm, and 5.382 cm, respectively.

The results indicated that complex ML models may not achieve superior performance metrics. Our investigation found that LR had the highest performance measures, higher than those of complex algorithms, such as SVM, RF and KNN. These suggested that the performance of ML depends on the training dataset, not the algorithm's complexity; thus, it is necessary to find a suitable ML model for solving this specific problem. Furthermore, it is widely recognized that the stature estimation model is specific to a particular population.

The results of this study indicated that the R^2 of the stature estimation model in this study was lower than those of the prior. The R^2 of the stature estimation model in the Italian, Chinese, and Japanese male populations ranged from 0.35 to 0.56[6,7,16,17]. However, the model's error rate could not be compared due to the different performance matrices from previous studies. The variation in outcomes may arise from differences in demographic characteristics, sample types (e.g., dry skeletons, CT scans), and variations in age and height distributions among the samples, which could impact the precision of the findings.

Even though the accuracy of stature estimation using the scapula dimension in a Thai population of this study was inferior to that of long bones[4], compared with the stature estimation model using non-long bones in the Thai population, stature estimation using the scapular indicated a higher R^2 value than that of the sternum. However, this was inferior to that of the calcaneus, clavicle, and sacrum[14,18,22,23.]

The limitations of this study were the relative number of scapula measurements and machine learning algorithms. In addition, it is specific to the male population of Southern Thailand; and was conducted using CT scans. That means different genders, populations, and types of samples may affect the results. Further studies of stature estimation using scapular bones by new measurements and other machine learning algorithms could be beneficial.

Conclusion

Utilizing PMCT of the scapular proved valuable in determining the stature of individuals in the Southern Thai male population. The machine learning algorithm demonstrated valuable tools for estimation stature. However, it is important to note that complicated machine learning models do not always result in better performance measures than non-complicated machine learning models.

Ethics approval of research

This study obtained approval from the ethics committees of both the Faculty of Medicine at Chiang Mai University (FOR-2565-0038) and Prince of Songkla University (REC. 66-024-19-4). The requirement for informed consent from each subject was waived.

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Conflict of interest

The authors declare no conflict of interest.

References

1. Christensen AM, Passalacqua NV, Bartelink EJ. Forensic anthropology: current methods and practice. 2nd ed. Philadephia: Elsevier; 2019.
2. Klepinger LL, Fundamentals of forensic anthropology. Vol. 1. Hoboken: Wiley; 2006.
3. DiGangi EA, Moore MK. Research methods in human skeletal biology. Philadephia: Elsevier; 2013.
4. Mahakkanukrauh P, Khanpetch P, Prasitwattanseree S, Vichairat K, Troy Case D. Stature estimation from long bone lengths in a Thai population. Forensic Sci Int 2011;210:e1-7.
5. Saukko P, Knight B. Knight's forensic pathology. 4th ed. Boca Raton: CRC Press; 2015.
6. Campobasso CP, Di Vella G, Introna F Jr. Using scapular measurements in regression formulae for the estimation of stature. Boll Soc Ital Biol Sper 1998;74:75-82.
7. Giurazza F, Del Vescovo R, Schena E, Cazzato RL, D'Agostino F, Grasso RF, et al. Stature estimation from scapular measurements by CT scan evaluation in an Italian population. Leg Med (Tokyo) 2013;15:202-8.

8. Torimitsu S, Makino Y, Saitoh H, Sakuma A, Ishii N, Hayakawa M, et al. Stature estimation in Japanese cadavers based on pelvic measurements in three-dimensional multidetector computed tomographic images. Int J Legal Med 2015;129:633-9.
9. Kalia S, Shetty SK, Patil K, Mahima VG. Stature estimation using odontometry and skull anthropometry. Indian J Dent Res 2008;19:150-4.
10. Krishan K, Kumar R. Determination of stature from cephalo-facial dimensions in a North Indian population. Leg Med (Tokyo) 2007;9:128-33.
11. Terazawa K, Takatori T, Mizukami K, Tomii S. Estimation of stature from somatometry of vertebral column in Japanese. Nihon Hoigaku Zasshi 1985;39:35-40.
12. Terazawa K, Akabane H, Gotouda H, Mizukami K, Nagao M, Takatori T. Estimating stature from the length of the lumbar part of the spine in Japanese. Med Sci Law 1990;30:354-7.
13. Torimitsu S, Makino Y, Saitoh H, Ishii N, Hayakawa M, Yajima D, et al. Stature estimation in Japanese cadavers using the sacral and coccygeal length measured with multidetector computed tomography. Leg Med (Tokyo) 2014;16:14-9.
14. Keereewan W, Monum T, Prasitwattanaseree S, Mahakkanukrauh P. Stature estimation using the sacrum in a Thai population. Anat Cell Biol 2023;56:259-67.
15. Jeamamornrat V, Monum T, Keereewan W, Mahakkanukrauh P. Stature estimation using the sternum in a Thai population. Anat Cell Biol 2022;55:170-8.
16. Torimitsu S, Makino Y, Saitoh H, Sakuma A, Ishii N, Hayakawa M, et al. Stature estimation in Japanese cadavers based on scapular measurements using multidetector computed tomography. Int J Legal Med 2015;129:211-8.
17. Zhang K, Cui JH, Luo YZ, Fan F, Yang M, Li XH, Zhang W, et al. Estimation of stature and sex from scapular measurements by three-dimensional volume-rendering technique using in Chinese. Leg Med (Tokyo) 2016;21:58-63.
18. Traithepchanapai P, Karnda M, Sukon P, Pasuk M. Stature estimation from dry bone and radiographic clavicular measurements in a Thai population. Med Health 2021;16:177-89.
19. Jasuja O, Singh G. Estimation of stature from hand and phalange length. J Indian Acad Forensic Med 2004;26:100-6.
20. Habib SR, Kamal NN. Stature estimation from hand and phalanges lengths of Egyptians. J Forensic Leg Med 2010;17:156-60.
21. CIFS, The 5th academic day. Stature estimation from calcaneal measurements in Thai. [monograph on the Internet]. Nakhon Pathom: CIFS; 2010 [cited 2024 Mar 30]. Available from: https://forensic.sc.mahidol.ac.th/proceeding/52_Sujitra.pdf
22. Nanagara P, Mahacharoen T, Navic P, Intasuwan P, Mahakkanukrauh P. Estimation of stature based on metatarsal bones in a Thai population. Int J Morphol 2023;1:2.
23. Scott S, Peckmann TR, Patriquin ML, Varas CG, Meek S. The estimation of stature from the tarsals: enhancing the disaster victim identification process in Thailand using the calcaneus and the talus. Forensic Anthropol 2018;2:332.
24. Ubelaker DH. Advances in forensic taphonomy. Boca Raton. CRC Press; 2002.
25. Mitchell T, Buchaman B, Dejong G, Dietterich T, Rosenbloom P, Waibel A. Machine learning. Annu Rev Comput Sci 1990;4: 417-33.
26. Czibula G, Ionescu VS, Miholca DL, Mircea IG. Machine learning-based approaches for predicting stature from archaeological skeletal remains using long bone lengths. J Archaeol Sci 2016;69:85-99.
27. Parlak ME, Özkul BB, Oruç M, Celbiş O. Sex and stature estimation from anthropometric measurements of the foot: linear analyses and neural network approach on a Turkish sample. Egypt J Forensic Sci 2024;14:18.
28. Knussmann R, Sperwien A. Sperwien, Relations between anthropometric characteristics and androgen hormone levels in healthy young men. Ann Hum Biol 1988;15:131-42.
29. Weatherall C. Morphological variation in the human scapula related to age & sex [Thesis]. Kansas: Wichita State University; 2020. Available from: https://soar.wichita.edu/items/58ce1186-da79-4447-9eed-86c772470072
30. De Mendonça MC. Estimation of height from the length of long bones in a Portuguese adult population. Am J Phys Anthropol 2000;112:39-48.
31. Arroyo M, Freire M, Ansotegui L, Rocandio AM. Intraobserver error associated with anthropometric measurements made by dietitians. Nutr Hosp 2010;25:1053-6.
32. Perini TA, Lameira G, Santos J, Palha F. Technical error of measurement in anthropometry. Rev Bras Med Esporte 2005;11:81-5.