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Artificial Neural Network: The Alternative Method to Obtain the Dimension of Ankle Bone Parameters

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Abstract: Current ankle morphometric measurement tools involve the use of radiographic techniques which may be unacceptable to many ethical committees due to the radiation exposure to subjects. In the present study, we propose an alternative method of ankle morphometric measurement using neural network computational model based solely on existing data measurements and demographic information. The reliability and prediction power of this technique were examined and compared with the morphometric measurements of normal subjects using Computed Tomography (CT) scan measurements and Multiple Linear Regression (MLR) method of prediction. The Artificial Neural Network (ANN) used in the present study was based on two-layer feed forward network. The network system included a hidden layer sigmoid transfer function and a linear transfer function in the output layer. For network training, standard levenberg-marquardt algorithm was used. The input used consisted of a set of demographic data (age, height and weight) while the output obtained from the analyses consisted of ankle morphometric measurements (Trochlea Tali Length (TTL) Talar Anterior Width (TaAW) Sagittal Radius of talar (SRTa) Tibia Length (TiL) Tibia Width (TiW) Width/Length Ratio of Talar (WLRTa) and Width/Length Ratio of Tibia(WLRTi)). The applicability and accuracy of these alternative methods were evaluated by comparing the predicted values from our computational analysis with the normal CT values of 15 randomly selected volunteers. Furthermore, our prediction values were also compared with the values predicted using the MLR method. The ANN method showed a greater capacity of prediction and was found to estimate the ankle joint morphometric measurements with a low percentage of error and high correlative values with the measurements obtained through the use of CT scan. In addition, the ANN method was also noted to be better in predicting ankle measurements than the MLR method as demonstrated by the lower average of standard deviations: SANN = 1.35, SMLR = 2.20 for females and SANN = 1.81, SMLR = 4.07 for males. The ANN method is potentially better alternative to predict ankle morphometric measurements than CT scan and MLR methods.

Key words: Artificial neural network, ankle bone parameters, CT scan data, demographic variables, multifactorial architecture

INTRODUCTION

Ankle morphometric databanks are important to establish a suitable ankle implants for a particular population. It has been suggested that due to changing regional altitude, climate, gender dominance and variations in the morphometric features of any given population an update in the ankle measurement databanks should be performed every 5 years (Yip *et al*., 1988). The morphometric measurements of the ankle can be obtained through the use of Computed Tomography (CT) scan, X-ray or direct measurements on cadavers. However, the major challenge in ensuring a databank remains updated is in obtaining adequate number of healthy volunteers who are willing to expose themselves to radiation such as those emitted during CT scan, Magnetic Resonance Imaging (MRI) or X-ray procedures (Balonov and Shrimpton, 2012; Brix *et al*., 2009; Gonzalez an Darby, 2004; Puustinen *et al*., 2012). Because of these limitations, some researchers prefer cadaveric studies to obtain the morphometric measurements of the ankle joint (Hatzantonis *et al*., 2011; Brenner *et al*., 2003; Tourret and

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Talkhani, 2004). However, data that can be obtained through cadaveric studies is difficult due to the limited availability of donors and shrinkage of macerated bones that are likely to affect the accuracy of morphometric measurements (Brenner *et al*., 2003). Thus, an alternative approach is needed to create a comprehensive database exclusively for ankle morphometric measurements.

Conventionally, the relationships between morphometric-dependent and demographic-independent measurements have been evaluated using multiple regressions. Similarly, till date, a variety of methods based on artificial intelligent techniques have been suggested as alternatives to statistical methods. These methods are claimed as universal predictors, especially to model highly nonlinear functional relationships between the demographic data and morphometric measurements. In the context of computational intelligence, soft computing is a promising approach that mimics the remarkable ability of the human mind (Bien and Song, 2003; Zadeh, 1994). In the last 25 years, Artificial Neural Network (ANN) has been used as an alternative to linear statistical methodology (Lukic *et al*., 2012). The major advantage of neural networks is that they are parallel, distributed and adaptive information processing systems that develop their functionality in response to exposure to information (Lukic *et al*., 2012; Penny and Frost, 1996). In addition, they use computerized artificial intelligence processes for classification and pattern recognition (Lukic *et al*., 2012).

Recently, critical care and trauma health care system have started employing ANN for outcome predictions (Pandey and Mishra, 2009; Schollhorn, 2004). However, till date, there are no published data that consider ANN as a tool for predicting ankle morphometric measurements. In this context we carried out the validation of a concept study regarding the use of ANN model for the prediction of ankle morphometric measurements. The primary aim of the study was to compare the power of prediction of ankle morphometric measurements using ANN with that of direct CT measurements and Multiple Linear Regression (MLR) analysis.

MATERIALS AND METHODS

This study was conducted on 100 adults aged between 20 and 38 years (50 females and 50 males). A total of seven morphometric measurements were obtained from each adult. The following ankle measurements were preferred: Trochlea Tali Length (TTL) Talar Anterior Width (TaAW) Sagittal Radius of Talar (SRTa) Width/Length Ratio of Talar (WLRTa) Tibia Length (TiL) Tibia Width (TiW) and Width/length Ratio of Tibia (WLRTi).

A CT scan of the ankles of each adult was used to reconstruct three-dimensional models of ankle joints using Mimics Software (Materialise NV). Furthermore, SolidWorks (Dassault Systemes Solid Work Corporation) was used to measure the morphometric parameters of the three-dimensional ankle model and standard deviations of the results, SANN and SMLR given by Eq. 1 and 2 were used to compare the performances of the methods, similar to that carried out in the study by Kaya *et al.* (2003):

$$S_{ANN} = \sqrt{\frac{\sum(\text{measured-ANN}_{\text{predicted}})^2}{\text{n-1}}} \quad (1)$$

$$S_{MLR} = \sqrt{\frac{\sum(\text{measured-MLR}_{\text{predicted}})^2}{\text{n-1}}} \quad (2)$$

MLR analysis: MLR analysis was performed using SPSS version 17.0 to examine the relationship between independent variables (age, height and weight) and dependent variables (TTL, TaAW, SRTa, WLRTa, TiL, TiW and WLRTi) for both sexes. In addition, MLR was also used to predict the ankle morphometric measurements which are the TTL, TaAW, SRTa, WLRTa, TiL, TiW and WLRTi. The accuracy of the MLR model was determined by comparing the predicted values with the actual measurements using CT scan.

ANN model: The ANN used in this study was a feed forward network with a hidden layer of sigmoid transfer function and an output layer of linear transfer function. The number of neurons in the hidden layer was selected from 2-30 through a trial-and-error process (Tu, 1996). The input to the neural networks includes age, height and weight. The TTL, TaAW, WLRTa, TiL, TiW and WLRTi was selected as targets. The training, validation and testing of the ANN model was performed using MATLAB software (The MathWorks, Inc., USA) with ANN tool box (Aghav *et al*., 2011). For network training, standardLevenberg-Marquardt algorithm was used.

In the ANN study, the data set consist of 100 subjects (50 females and 50 males) were randomly divided into three equal parts as training, validation and test data. The training sample (70 subjects) was presented to the network during training while the validation sample (15 subjects) was used to measure network generalization and stop training when the generalization stopped improving. The testing sample (15 subjects) had no effect on training and hence, provided an independent measure of network performance during and after training. The mean squared error was employed as the performance measure during training (Mukherjee and Routroy, 2012). The accuracy of the ANN model was determined by comparing the predicted values with the actual measurements using CT scan.

RESULTS AND DISCUSSION

The mean and standard deviation of the descriptive values related to the measurements are presented in Table 1. The seven outputs (TTL, TaAW, SRTa, TiL, TiW, WLRTa and WLRTi) required for ankle implant design were selected for prediction purposes. The data of the two groups were evaluated separately. The results o f the analysis for both the gender are shown in Table 2 and 3, respectively. Comparisons were made between the multiple regression equation of morphometric measurement for females (Table 2) and males (Table 3). The results demonstrated that the dependent measurements for males and females were the same while the regression equation for the morphometric measurements was different. In general, the coefficient of determination (R^2) values of the regression equations obtained was noted to be quite similar for both groups, except for TiL and TiW. The TiL of males was noted to be greater than that of females with males exhibiting the highest R^2 values while the TiW of females was observed to be greater than that of males with females exhibiting the highest R^2 values. On the other hand, the lowest R^2 values for both groups were either both in the WLRTa or WLRTi. Apart from these two outputs, the regression equation was not found to be statistically significant ($p>0.05$).

As shown in Table 4, the ANN performances were found to be better than the performances of the MLR method in all predicted outputs for both females and males ($p<0.05$), since lower standard deviation means a better prediction capability (Kaya *et al*., 2003). The comparison of the performance of ANN method to MLR method based on the average percentage errors and the correlation coefficients of predicted morphometric measurements to the actual values of ankle morphometric measurements are summarized in Table 5. It can be observed from the table that the lowest percentage error (0.04%) whilst the highest percentage error (7.52%) was observed using MLR method. On the other hand, the highest correlation was determined between the predicted measurement and actual measurement value of CT scan (0.96) for WLRTi of females using ANN method while the lowest correlation coefficient (0.15) was found for WLRTi of females using the MLR method.

Table 1: Morphological measurements of the talocrural join for males and females (measurement were expressed in mm)

Morphological measurement	Confidence interval (90%) Gender	Mean	SD
TTL	Female	31.93	2.11
	Male	36.20	2.40
TaAW	Female	28.38	1.68
	Male	32.36	2.36
SRTa	Female	20.20	2.20
	Male	22.50	2.70
TiL	Female	31.00	1.80
	Male	36.52	2.00
TiW	Female	29.60	1.50
	Male	32.00	2.10
TaA W/TTL ratio	Female	0.897	0.04
	Male	0.895	0.08
TiW/TiL ratio	Female	0.882	0.04
	Male	0.877	0.05

Table 2: Regression equations between ankle morphometric parameters for female

Regression equations	F-values	R^2
$Y = a+b_1X_1+b_2X_2+...b_pX_p$		
TTL = -2.66+0.027 (age)+0.199 (height)+ 0.061 (weight)	5.44*	0.37
TaAW = -5.932+0.191 (age)+0.175(height)+ 0.054 (weight)	5.99*	0.39
SRTa = 2.897-0.029 (age)+0.125 (height)- 0.039 (weight)	5.21*	0.36
TiL 7.835-0.082 (age)+0.152 (height)+ 0.027 (weight)	3.00*	0.24
TiW = -6.133+0.060 (age)+0.197 (height)- 0.032 (weight)	9.06*	0.49
WLRTa = 0.811+0.005 (age)	0.55	0.06
WLRTi = 0.476+0.004 (age)+0.002(height)	0.79	0.08

*Significance difference at level $p<0.05$

Table 3: Regression equations between ankle morphometric parameters for male

Regression equations	F-values	R^2
$Y = a+b_1X_1+b_2X_2+...b_pX_p$		
TTL = 3.298+0.005 (age)+0.216 (height) +0.05 (weight)	6.93*	0.37
TaAW = -7.993+0.056 (age)+0.233(height)-0.008 (weight)	5.95*	0.34
SRTa = 0.359+0.039 (age)+0.121 (height)-0.032 (weight)	6.79*	0.37
TiL 0.92-0.04 (age)+0.212 (height)+0.009 (weight)	8.86*	0.43
TiW = 10.688+0.07 (age)+0.151 (height)-0.035 (weight)	2.90*	0.21
WLRTa = 0.577+0.001 (age)+0.001 (hight)+0.0001 (weight)	2.69	0.19
WLRTI = 1.194+0.001 (age)-0.0001 (height)- 0.0001 (weight)	1.19	0.09

*Significance difference at level $p<0.05$

Table 4: Comparative performance of output predicted by Artifical Neural Network (ANN) and Multiple Linear Regression (MLR)

Output	Gender	S_{ANN}	S_{MLR}
TTL	Female	1.96	3.67
	Male	3.01	5.26
TaAW	Female	2.71	3.53
	Male	2.46	6.32
SRTa	Female	1.40	2.05
	Male	1.80	3.75
TiL	Female	2.06	3.57
	Male	2.44	4.68
TiW	Female	1.21	2.39
	Male	2.79	7.98
WLRTa	Female	0.07	0.13
	Male	0.05	0.28
WLRTi	Female	0.02	0.08
	Male	0.09	0.24
Means	Female	1.35	2.20
	Male	1.81	4.07

Table 5: The average percentage errors and the correlation coefficient pf predicted morphometric measurements to the actual valus of ankle morphometric measurement

		Female		Male	
Morphometrie features	Methods	Percentage error (%) (min. error-max. error)	Correlation coefficient	Percentage error (%) (min. error-max. error)	Correlation coefficient
TTL	ANN	1.88 (0.13-60.60)	0.93	1.76 (0.09-5.04)	0.85
	MLR	3.64 (0.94-7.52)	0.83	3.66 (0.12-14.57)	0.64
TaAW	ANN	0.33 (0.00-7.81)	0.86	1.75 (0.00-13.34)	0.82
	MLR	3.92 (0.92-8.85)	0.68	4.72 (0.07-9.88)	0.68
SRTa	ANN	2.51 (0.00-7.14)	0.89	2.33 (0.00-11.91)	0.88
	MLR	4.84 (1.34-10.07)	0.70	4.85 (0.50-11.15)	0.66
TiL	ANN	2.04 (0.05-8.73)	0.86	1.64 (0.00-7.61)	0.84
	MLR	3.70 (0.24-12.42)	0.54	3.32 (0.10-9.47)	0.78
TiW	ANN	1.34 (0.00-7.16)	0.90	0.04 (0.00-0.15)	0.78
	MLR	3.69 (0.2-9.22)	0.55	6.36 (0.67-20.03)	0.37
WLRTa	ANN	2.03 (0.00-5.74)	0.84	1.34 (0.00-8.24)	0.93
	MLR	4.58 (1.09-13.58)	0.26	7.52 (0.00-14.43)	0.33
WLRTi	ANN	0.47 (0.00-2.41)	0.96	1.70 (0.00-18.12)	0.90
	MLR	3.45 (0.00-8.69)	0.15	7.15 (0.00-18.12)	0.33

ANN and MLR are highly accurate predictive methods and have the potential to be used as an assisting tool in ankle implant design. Theoretically, ANN has the advantage of predicting the outcome variable; in particular, the major advantage includes the capability to identify complex nonlinear relationships between the outcomes and predictive factors. ANN has the ability to include all major interactions between the predictors, tolerance of noisy or incomplete input data and various types of learning algorithm strategies (Chen *et al*., 2009). However, some disadvantages include low efficiency of interpretability at the level of individual predictors, its disposition to over-fitting and the requirement of optimizing methods to frame a comprehensive network (Chen *et al*., 2012; Ayer *et al*., 2010; Pai *et al*., 2012). On the other hand, MLR analysis is capable of estimating the probability of the outcome of interest and is superior in examining the probable relationships between independent and dependent variables (Chen *et al*., 2012). Furthermore, as it can provide a quantitative description of the predictors on outcome variables, it has been widely employed in epidemiologic studies (Tu, 1996; Ottenbacher *et al*., 2004; Shah *et al*., 2005).

Fundamentally, different approaches are used in both the ANN and regression methods. Until now, several studies have compared the predictive and diagnostic abilities of these methods. A meta-analysis comparing the ANN with regression models demonstrated that ANN outperformed regression models in 36% of the cases while regression models outperformed ANN in 14% of the cases. Interestingly, these two methods were reported to exhibit comparable performance in the remaining 50% of the subjects (Chen *et al*., 2012). Among the 12% studies comparing the performance of ANN with the back-propagation algorithms and regression method for software guided clinical diagnosis (Caocci *et al*., 2010; Lin *et al*., 2006; Agatonovic-Kustrin and Beresford, 2000; Bartfay *et al*., 2006; Behrman *et al*., 2007) and Eftekhar *et al*. (2005) concluded that ANN exhibits a higher diagnostic performance than the regression method while the other half (Ottenbacher *et al*., 2004; Shah *et al*., 2005; Caocci *et al*., 2010; Jaimes *et al*., 2005; Jardin *et al*., 2009; Kazemnejad *et al*., 2010; Lin *et al*., 2010) concluded that the two methods have similar performance.

In the present study when compared to the MLR method, the ANN method was found able to predict the outcome variable accurately. The reason behind this may lie in the accuracy of the ANN method. It may be the case that use of the sigmoid function to construct the predicted equation might have provided the accuracy in the prediction modeling. In general, the use of polynomial formula in MLR analysis has been reported to limit its capability to develop objective formula when compared with the ANN method (Hsu *et al*., 2011). Although, the MLR models are easily applied, its reliability declines as the problems become more complicated. For example, the MLR method that was applied in the present study could predict the outcome variables having strong linear relation with the dependent variables but failed to predict the accurate outcome variables having low linear relation with the dependent variables such as WLRTa and WLRTi. However, these two outcome variables were accurately predicted by the ANN method and the average percentage error was low with respect to the CT scan measurement values (1.34 and 0.47%, respectively). Thus, the low percentage error and high correlation with the CT scan measurement values prove the prediction power of the ANN method.

The ANN is a nonlinear statistical data modeling tool (Liu *et al*., 2000; Seyhan *et al*., 2005; Song *et al*., 2005) which provides a flexible formula to fit the outcome of a problem by increasing the number of neurons in the hidden layer or by using a multi-layered ANN architecture (Hsu *et al*., 2011). As a result, this method could predict the accurate outcome variables that have a low linear relation with the predictors. Furthermore, the ANN method has been observed to be superior to the MLR method and the ANN models should be used appropriately to avoid overlearning or insufficient learning because these learning issues might affect the precision of the models (Hsu *et al*., 2011).

CONCLUSION

In conclusion, the ANN method demonstrated a greater capacity of prediction and is able to estimate all the ankle joint morphometric measurements with low error percentage and high correlation with the actual measurement values of CT scan. In addition, the ANN method also performed better than the MLR method in terms of its prediction accuracy. With the avoidance of radiation and its high predictability of ankle morphometry, our study demonstrates that within certain limitation ANN can potentially be used as a preferred alternative to radiological measuring techniques.

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