Application of Artificial Neural Network on Body Somatotype Analysis among Indian Population

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ABSTRACT

This study aims to verify the accuracy of the body somatotype analysis of the anthropometric measurements by using multi-layer perceptron Artificial Neural Network (MLP-ANN) model. It would also compare the predictive accuracy with a linear regression model using anthropometric body somatotype analysis (endomorphy, mesomorphy and ectomorphy) as reference method.

A total of 293 persons (126 men and 167 women), between the ages of 19-40 years were recruited. The body somatotype was calculated from the anthropometric measurements using Heath-Carter technique. Linear regression equations and MLP-ANN prediction equations were developed.

The variables - age, height, weight, humerus and femur breadth, arm and calf circumferences, subscapular, suprailiac, supraspinale and medial calf skinfold thicknesses, and sex as covariate, were used to develop the linear model (LR) to predict EndomorphyLR (coefficient of determination, R^2=0.891; standard error of estimate (SEE) = 0.387), MesomorphyLR (coefficient of determination, R^2=0.998; SEE = 0.068) and EctomorphyLR (coefficient of determination, R^2=0.871; SEE = 0.553). The above variables were placed in the input layer of the MLP-ANN model (EndomorphyMLP, R^2=0.909; MesomorphyMLP, R^2=0.985; EctomorphyMLP, R^2=0.994).

The result reflects that MLP-ANN model had greater accuracy in predicting endomorphy and ectomorphy when compared to the linear model. However, linear model showed better accuracy for mesomorphy. Therefore, MLP-ANN model is more suitable in predicting body somatotype (endomorphy and ectomorphy) among population.

Key words: Anthropometry, Somatotype, Artificial Neural Network, Multilayer Perceprton

INTRODUCTION

Measuring anthropometric dimensions of the human body provide a metric description about body size and body type. It is useful in various applications including defining body growth and development and nutritional status, environmental adaptation, forensic application, anthropological traits, and also particularly in sports applications [1].

Somatotyping is a classification to appraise human body shape and composition, expressed as three-number rating representing endomorphy (relative fatness), mesomorph (relative musculoskeletal robustness) and ectomorphy (relative linearity of a physique) components respectively. It thus, surmises the estimates of body composition and shape. Somatotypes are useful for description and comparison of populations and for monitoring growth and ageing changes. There are various methods to set the criteria of somatotyping, e.g., a) anthropometric method, in which body dimensions are used, b) photoscopic method, by rating standardized photograph of an individual, and c) combination of anthropometric and photoscopic methods. However, anthropometric method has proven to be the most useful for a wide variety of applications [2].

With the increase in modernization and lifestyle changes, people are at elevated risk of cardiovascular as well as metabolic disorders [3, 4]. In a study among students of age group of 15-18 years during 1984-85 and 2009-10, significant difference was observed in all variables of somatotype. Men who fell under balanced mesomorph type during 1984-85 transformed to mesomorph-endomorph type during 2009-10. Similar was the results for women. Considering the enormity of the application of body type assessment, the precision and accuracy of the measurement and results has critical importance.

Studies have investigated various measurements of body composition with artificial neural network [5, 6, 7]. These studies have shown that the ANN model performed better in predictive accuracy than linear regression model. Like so, it would be interesting to explore out whether the ANN model exhibits greater precision and accuracy in predicting body type than the linear regression model.

Derived from several disciplines, including statistics, data mining is the science of searching large data sets for important and unsuspected patterns and structures. Data mining combines statistical methods and artificial intelligence in two ways - exploratory data analysis to find new associations and use of inferential statistics to rule out chance [8]. Artificial Neural Networks (ANN) are widely used algorithms in many applications and are modelled based on biological neural systems. For classification, the model is trained in such a way that input and output nodes are connected with a set of weighted links based on input-output association of training data. The multilayer perceptron algorithm is the most popular learning algorithm applied in ANN to learn the model by adjusting the weights of the node by minimizing the total sum of squared errors [9].

In the present study, we measured anthropometric variables to determine the body type. The multilayer perceptron algorithm was then applied to come up with a predictive model and compare the results with a linear regression model to determine the better predictor with greater accuracy.

MATERIALS AND METHODS

126 men and 167 women, between the ages of 19-40 years (men: mean=21.9±2.9; women: mean=21.8±2.7) from Gujarat, India participated in the study. All the volunteers were healthy and free from any physical abnormalities. Participants were informed of the purposes of the study and signed the written informed consent.

Self-informed age and lifestyle habits were recorded. Stature was measured with a portable stadiometer (Holtain Ltd., Crosswell, Crymych, UK) and weight was measured while bare foot on a digital weighing scale with sensitivity of 0.1 kg. Biepicondylar breadths of the humerus and femur were measured with a bone caliper (UNA & Co., India). The circumferences of the chest, waist, hip, thigh and calf were measured with a non-elastic measuring tape. The skinfold measurement (biceps, triceps, subscapular, suprailiac, supraspinale and medial calf) were measured as per standard protocol with a skinfold caliper (Holtain Ltd., Crosswell, Crymych, UK). All the measurements were performed by one male and female trained researcher.

Heath-Carter technique was used to determine the three components of somatotype – endomorphy, mesomorphy and ectomorphy. Ten anthropometric parameters were used for determining the somatotype (weight; stature; triceps, subscapular, supraspinale, and calf skinfolds; humerus and femur widths; and biceps and calf girths). The measurements were taken as per the procedure as described in Marfell-Jones M (1991) [10]. The somatotype calculation and analysis software from Sweat Technologies [11] was used.

Linear regression was obtained using age, height, weight, humerus and femur breadth, arm and calf circumferences, subscapular, suprailiac, supraspinale and medial calf skinfold thicknesses as independent variables, sex as the factor, and the somatotypes (endomorphy, mesomorphy and ectomorphy) as the dependent variables.

The same dataset was then processed by multilayer perceptron algorithm. It separated into three classes: input units, which receive information to be processed; output units, where the results of the processing are found; and units in between known as hidden units. The architecture is depicted in Fig 1. In the input unit sex, age, height, weight, humerus breadth, femur breadth, arm circumference, calf circumference, subscapular skin folds, suprailiac skinfold, supraspinale skinfold, medial calf skinfold were used as attributes. The aim of this study was to measure the prediction accuracy of ANN for the endomorphy, mesomorphy, ectomorphy. Therefore, endomorphy, mesomorphy, ectomorphy was considered as output units. A single hidden layer with eight hidden units was used. The neural network architecture determined 72.7% training sample and 27.3% testing sample for learning procedure. The learning procedure was performed till the consecutive step(s) with no decrease in error value was attained. Sum of squares error function was used to measure the errors. After the training process, the optimal weight matrixes and the bias vectors for the input unit and hidden unit were obtained separately for the endomorphy, mesomorphy and ectomorphy. These optimal weight matrixes and bias vectors predict endomorphy, mesomorphy and ectomorphy values without training the MLP-ANN.

Further, regression model was used to take the input unit as predictor variables and output unit as dependent variables for comparing the result of ANN and regression model.

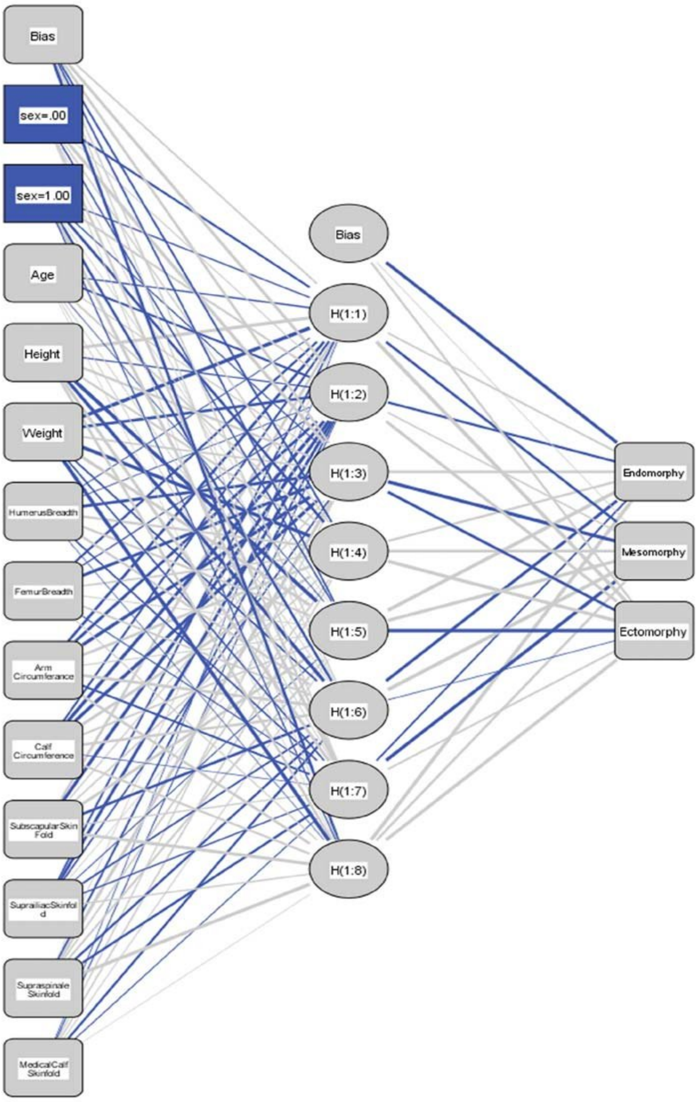

Fig 1: Architecture of multilayer perceptron learning technique.

RESULTS

The anthropometric variables and the somatotypes for men and women studied are given in Table 1. The data reveals that significant difference in the entire variable measured exist between both the sexes, except that of age.

The variables used to develop the linear model (LR) to predict EndomorphyLR (coefficient of determination, R^2=0.891; standard error of estimate (SEE) = 0.387), MesomorphyLR (coefficient of determination, R^2=0.998; standard error of estimate (SEE) = 0.068) and EctomorphyLR (coefficient of determination, R^2=0.871; standard error of estimate (SEE) = 0.553).

Further, for MLP-ANN, the whole dataset was used with sex as factor attribute. The variables, as used in the linear regression model were placed in the input layer of the MLP-ANN model and the somatotypes were obtained. The coefficient of determination of the estimated EndomorphyMLP, measured was R^2=0.909; for MesomorphyMLP, R^2=0.985; and for EctomorphyMLP, R^2=0.994). The results when compared with the linear model shows that EndomorphyMLP and EctomorphyMLP have higher coefficient of determination than the LR, however for mesomorphy, LR shows better result (Fig 2), corroborating with the results of the study by [12].

Table 1: Statistic of anthropometric variables for men and women.

Attribute	Men		Women		p
	Mean	SD	Mean	SD	
Age	21.9	2.7	20.8	2.9	NS
Height (cm)	171	6.2	155.2	6.3	0.001
Weight (kg)	60.8	11.5	50.1	8.3	0.001
Humerus Breadth (cm)	6.8	0.4	5.8	0.3	0.001
Femur Breadth (cm)	8.9	0.7	8.1	0.4	0.001
Arm Circumference (cm)	27.5	3.3	23.7	2.2	0.001
Calf Circumference (cm)	32.8	4.8	29.9	2.6	0.001
Subscapular Skinfold (mm)	11	3.7	11.5	3.7	NS
Suprailiac Skinfold (mm)	9.7	4.7	12.5	5.3	0.001
Supraspinale Skinfold (mm)	12.7	4.5	13.6	5.6	NS
Medial Calf Skinfold (mm)	9.6	4	14.5	3.9	0.001
Endomorphy	3.3	0.9	4.3	1.2	0.001
Mesomorphy	3.4	1.7	2.8	1	0.001
Ectomorphy	3.4	1.5	2.7	1.4	0.001

NS: Not significant

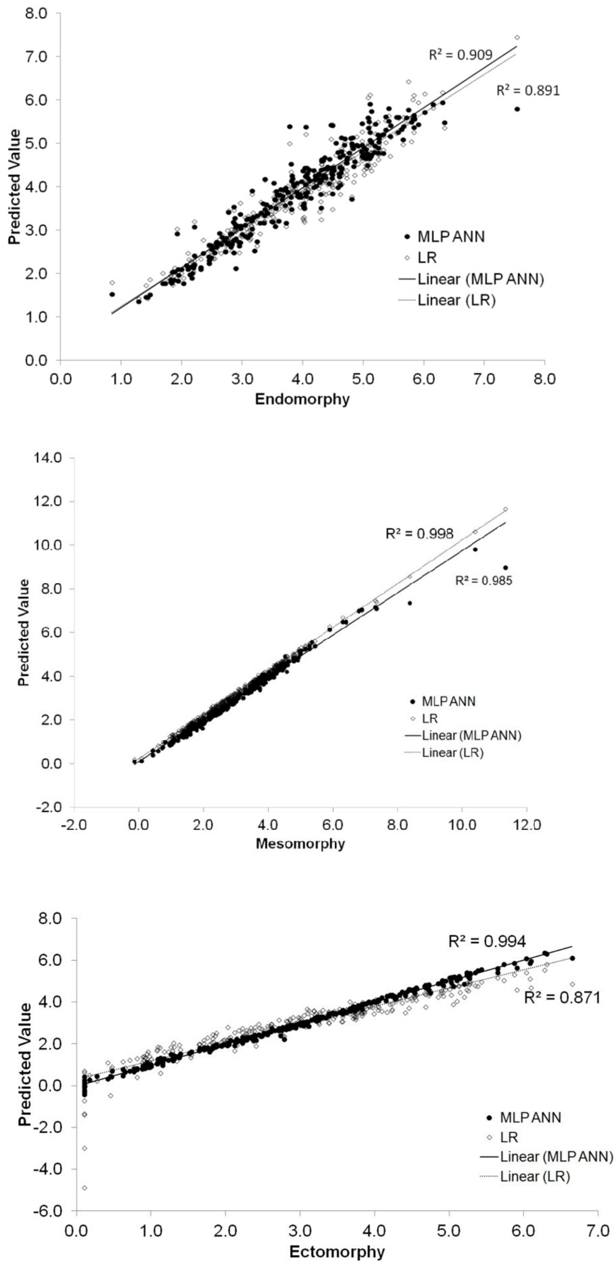

Fig 2: Relationship between EndomorphyMLP, MesomorphyMLP and EctomorphyMLP and the calculated Endomorphy, Mesomorphy and Ectomorphy by Heath-Carter technique.

DISCUSSION

This study attempted to understand the prediction performance in estimating the somatotypes among Indian population using the MLP-ANN model as well as the linear regression model. The same data set along with same number of attributes were used in both the models for comparison. The calculation of somatotype require 11 anthropometric variables (Table 1) [11], therefore 11 neurons were used for the prediction models, wherein endomorphy and ectomorphy came out as better predictor using the MLP-ANN model and mesomorphy as better predictor by LR model.

The results of the present study were in line with other studies which reiterate that using more number of neurons results in higher coefficient of determination [5, 12]. Linder et al. [6] also states that multiple variables must be taken into account which comparing results of ANN and classical statistical models. The relationship between input and output is defined by an activation function which along with the weighted links decides the behaviour of the ANN. Linear, sigmoid (logistic) and hyperbolic tangent function or other activation function can be used in the multilayer perceptron learning algorithm. A hyperbolic tangent function was used in this study, as it performs better recognition accuracy than other functions [13]. As found, the neural network architecture determining 72.7% training sample, which comprises of data records to train the neural network; some percentage of cases in the dataset be assigned to the training sample in order to obtain a model. The testing sample, determined as 27.3% is an independent set of data records used to track errors during training in order to avoid overtraining [14].

In the present endeavour, one hidden layer was adopted, although there was no difference in the output using more than one hidden layer. Literature also reveals that generalized rule for number of hidden layers to be constructed in MLP-ANN does not exist [5].

In conclusion, the result reflects that MLP-ANN model had greater accuracy in predicting endomorphy and ectomorphy when compared to the linear model. However, linear model showed better accuracy for mesomorphy. Therefore, MLP-ANN model is more suitable in predicting body somatotype (endomorphy and ectomorphy) among Indian population.

STATEMENT OF RELEVANCE

ANN on body somatotype is a novel application of data mining to assess the body physique. It would be relevant in health and fitness research, evaluation of body composition, nutritional status and disorders, body growth and health risks, as well as performance analysis in sports. Such model may be incorporated as a pragmatic measuring tool in future allied research.

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