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Estimation of Tibia Length in Turkish Adults Using the Artificial Neural Network Method

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Abstract; Of all the long bones in the human skeleton, the bone fractured most often is the tibia. In the surgical treatment of shaft fractures, the use of the correct length nail is important. Therefore, the length of the tibia is crucial during orthopedic surgery and in forensic science, anatomy and anthropology. In this study, the Artificial Neural Network (ANN) method was applied to obtain a correct estimation of the tibia length from its proximal measurements. The inputs of the ANN, which are independent parameters of the problem, are the age of the subject, the tibia side, top measurement, middle measurement, bottom measurement and fibula length. A total of 193 tibia bone measurements were taken from an adult Turkish population. Five different input parameter combinations were tried for the correct determination of the tibia length. According to these combinations, the root mean square error (RMSE) values and correlation coefficients ® were obtained as 21.27, 17.60, 19.56, 18.39, 6.14 and 0.66, 0.78, 0.72. 0.76, 0.98 for the training data of ANN, respectively. For the test data these values were 21.81, 21.53, 23.32, 21.50, 9.26 for RMSE and 0.51, 0.56, 0.44, 0.55, 0.93 for values. The correlation coefficients showed a moderate correlation between data in the ANN estimation, and according to the RMSE values, the error in the estimations was at the level of approximately 5%.

INTRODUCTION

The tibia is the bone most frequently fractured of all the long bones [1]. Intramedullary nailing is the most preferred surgical treatment for shaft fractures [1]. In this operation, the use of the correct length nail is important for satisfactory results. Although there is no standard method for measuring tibial length [2], many methods for tibial length measurement have been defined in the literature. These are mainly intraoperative techniques, radiological techniques and anthropometric measurement techniques [3]. The length of the tibia is as important during orthopedic surgery as in other disciplines, primarily forensic medicine, anatomy and anthropology. Accurate measurement of tibia length or estimation of this length is used in many other places such as body length calculation from the bone [4].

The proximal tibia is the region less affected by the trauma of shaft fracture [1]. In addition, the proximal tibia is one of the skeletal regions that is well preserved after death. Information obtained from body parts can be important in the identification of disaster victims [5]. The calculation of full body height from the same AP radiological image of the tibia also has the advantage of reducing costs and the need for additional radiological imaging.

In recent years, the artificial neural network (ANN) method has been used in the field of orthopedics [6]. In the medicine field, several examples can be given for ANN, such as the neural network prediction of the movement of the lower extremities using angle-angle diagrams [7], medical imaging [8], medical disease prediction [9], automated detection and classification of proximal humerus fracture [10], improving bone strength prediction in human proximal femur specimens [11], bone fracture healing assessment [12], determination of patellar position [13], and estimation of femur length from the proximal measurements [14]. The ANN method is a mathematical model that mimics the human brain functionality. In the method, there is no need for any relationship between the input and output data. In the current study, six measurements of the tibia bone were collected to set feature set combinations that were used as input parameters for ANN. The main task was to obtain tibia length (TL) according to the given independent variables. According to the results, the ANN method was seen to be suitable for prediction of the tibia length. The second aim of the

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study was to show the utility of the method in the orthopedics field.

MATERIAL and METHODS

Ethics approval

Approval for the study was granted by the Local Ethics Committee (Sivas Cumhuriyet Univercity no: 2019-10/32, date: 09,10,2019).

Samples and measurements

Evaluations were made of 220 tibia AP radiographs. Any radiographs that were not completely AP or were not taken from the appropriate distance were excluded. Finally, 193 tibia bone measurements were used, which had been taken from an adult Turkish population. The measurements were taken on the radiological images of the tibia AP view (Fig. 1). Of the total samples, 106 were of the right leg and 87 of the left leg. The measurements were taken as 3 transverse diameters and 2 cm full-length measurements of the tibia and fibula, starting at the top of the tibia AP radiograph.

Artificial neural network (ANN)

Artificial neural network (ANN) [15] is a mathematical model that mimics the human brain functionality and nervous system in order to perform estimations for given problems. ANN consists of neurons which are the main processing units. The neurons are grouped in three different layers of input, hidden and output layers, with input, hidden and output neurons. Each neuron is connected to all the next layer neurons via adjustable synaptic weights. Data is transmitted from one neuron to another through these connections. For each independent variable of the problem there is an input neuron. After transmitting the data to hidden neurons, the data is summed and activated by the appropriate functions. The output of the hidden neurons is transmitted to output neurons and the dependent results are obtained, which is the aim of the calculations. In the hidden neurons, generally a sigmoid-like activation function is used. In this study, the tangent hyperbolic (*tanh = (ex - e-x)/(ex + e+x)*) activation function was used for hidden neuron activation. The numbers of the input and output neurons are related to the independent and dependent variables, whereas the numbers of hidden layers and their neurons depend on the nature of the problem. Generally, one hidden layer is enough for almost all problems. The hidden neuron number is determined after several trials because there is no rule for this determination. One of the ANN structures used in this study is shown in Fig.2. The input neurons (FL- fibula length, A- age, S - side, T- top measurement, M- middle measurement and B- bottom measurement) correspond to different variables for the problem.

The ANN method is composed of two main steps. In the training step, the weights are modified until an acceptable error level is reached by given input and output data to the network. In this study, the error function which measures the difference between desired and network outputs was the root mean square error (RMSE) given by the equation (1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - f_i)^2}{N}}$$

where *yi* and *fi* are the neural network and actual outputs, respectively, *N* is the total number of samples. After the determination of the final weights in the training step, the ANN is constructed. In the second step of ANN which is the test step, ANN is tested using the previously unseen test data. If the results are good, it is said that the constructed ANN has generalized the data, and the constructed ANN can be confidently used as appropriate for another set of data related to the given problem.

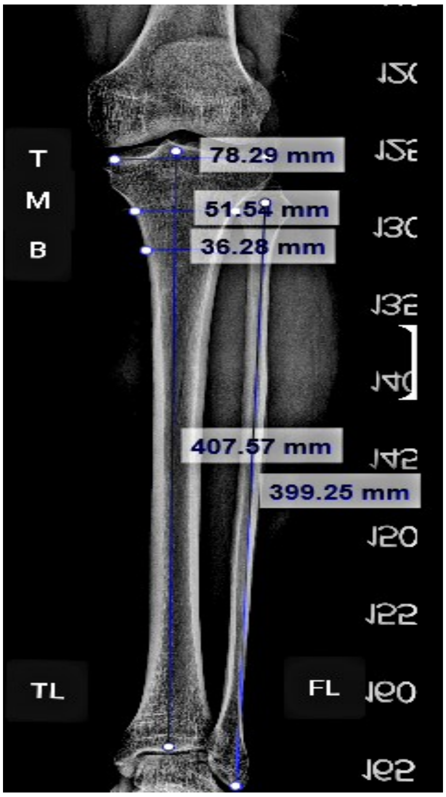

Figure 1. Radiological images of the tibia AP view. Tibia Length (TL), top measurement (T), middle measurement (M), bottom measurement (B) and fibula length (FL).

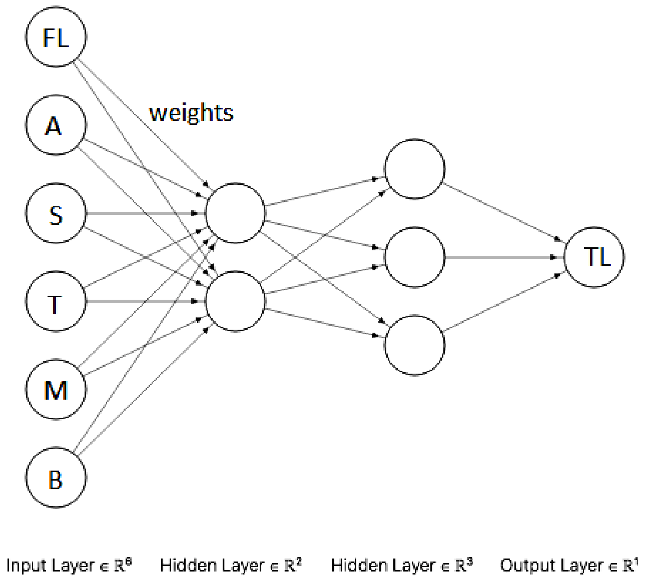

Figure 2. The 4-2-3-1 structure of ANN that was used

RESULTS and DISCUSSION

After several trials for this problem, it was seen that two hidden layers with two and three neurons structure gave the best results. Layered feed-forward ANN was used to estimate the length of the tibia (TL). All possible inputs were the age of the subject (A), the side of the tibia (S), top measurement (T), middle measurement (M), bottom measurement (B) and fibula length (FL). Different input combinations (Table 1) were tested and the results of all of these are presented. The total number of synaptic weights was calculated according to Eq. (2).

$$w = p \times h_1 + h_1 \times h_2 + h_2 \times r$$

where p, h_1, h_2 and r are neuron numbers in input, first hidden, second hidden and output layers, respectively.

Table 1. Different ANN properties used in this study

Name	Inputs*	Outputs	Total weights	ANN Structure
Type-I	T, M, B	TL	15	3-2-3-1
Type-II	A, T, M, B	TL	17	4-2-3-1
Type-III	S, T, M, B	TL	17	4-2-3-1
Type-IV	A, S, T, M, B	TL	19	5-2-3-1
Type-V	FL, A, S, T, M, B	TL	21	6-2-3-1
*Tibia length (TL), age (A), side (S), top measurement (T), middle measurement (M), bottom measurement (B) and fibula length (FL).				

*Tibia length (TL), age (A), side (S), top measurement (T), middle measurement (M), bottom measurement (B) and fibula length (FL).

All data were partitioned into two separate sets, for training and test stages. In this study, 80% of all data (153 data points) was used for training and 20% (40 data points) was used for the test. In the ANN training stage of this study, a back-propagation algorithm with Levenberg-Marquardt [16, 17] was used. The average values of the tibia length used in the training and test steps were obtained as 383.84 and 390.72 mm, respectively. The corresponding root mean square errors were 14.0 and 14.5 mm in the measurements of the radiological images, corresponding to an average error of approximately 3.5%.

In Type-1 ANN calculations, the RMSE value was obtained as 21.27 mm for the training data. In the left upper panel of Fig.2, the differences between measured TL and ANN estimated TL are shown. It can be seen from the figure that the maximum and minimum deviations from the measured values are 43.07 and 0.12 mm, respectively. The correlation coefficient for the training data was 0.66. For TYPE-II calculations (right upper panel of Fig.2), age information was added to the inputs. In this case, the maximum and minimum deviations from the measured values were 43.01 and 0.08 mm, respectively. The correlation coefficient for the training data was 0.78. The RMSE value was obtained as 17.60 mm. According to the result, it can be said that the age information improves the results. In the next calculation (Type-III), the information of the side of the bones was added. The maximum and minimum deviations from the measured values were obtained as 46.28 and 0.13 mm, respectively. The RMSE value was determined as 19.56 mm. The correlation coefficient for the training data was 0.72. As can be seen in the left middle panel of Fig.2, adding the side information to Type-I worsened the results. For TYPE-IV calculations (right middle panel of Fig.2), A, S, T, M, B data were the inputs. In this case, the maximum and minimum deviations from the measured values were 42.57 and 0.16 mm, respectively. The correlation coefficient for the training data was 0.76. The RMSE value was obtained as 18.39 mm. According to the result, it can be said that adding age and side information simultaneously caused worse results. In the final calculation of Type-V at the bottom of Fig.2, very good results were obtained after including FL data to the inputs. The maximum and minimum deviations were 21.34 and 0.0008 mm, respectively. The RMSE value was 6.14 mm and the correlation coefficient for the training data was 0.98.

To be able to see the overall success of the ANN method in TL estimation, the constructed ANN was tested on the test data which had not been used in the training process. For Type-1 ANN calculations, the RMSE was 21.81 mm. In the left upper panel of Fig.3, the ratio of measured TL to ANN estimated TL is given. It can be seen from the figure that the maximum and minimum deviations from the measured values were 51.90 and 0.073 mm, respectively. The correlation coefficient for the test data was 0.51. In TYPE-II calculations (right upper panel of Fig.3) with age information added to the inputs, the maximum and minimum deviations from the measured values were 50.24 and 0.25 mm, respectively. The correlation coefficient for the data was 0.56. The RMSE value was obtained as 21.53 mm. According to the result, it can be said that the age information had no effect on the results in the test data. In the next calculation (Type-III), information of the side of the bones was included. The maximum and minimum deviations from the measured values were 50.26 and 1.22 mm, respectively. The RMSE value was obtained as 23.32 mm. The correlation coefficient was 0.44 which showed that adding side information to Type-I slightly worsened the results (left middle panel of Fig.3). For TYPE-IV calculations (right middle panel of Fig.2), A, S, T, M, B data were used as inputs. In this case, the maximum and minimum deviations from the measured values were 50.85 and 0.075 mm, respectively. The correlation coefficient for the test data was 0.55. The RMSE value was obtained as 21.50 mm. In the final calculation of Type-V at the bottom of Fig.3, very good results were obtained after including FL data to the inputs. The maximum and minimum deviations were 22.45 and 0.28 mm, respectively. The RMSE value was obtained as 9.26 mm. The corresponding correlation coefficient for the test data in this case was 0.93. It was observed in the test data that the results from the first four types of ANN according to the different input parameters used in this study were quite similar to each other. Thus, with the exception of FL, adding parameters to the inputs did not improve the estimations.

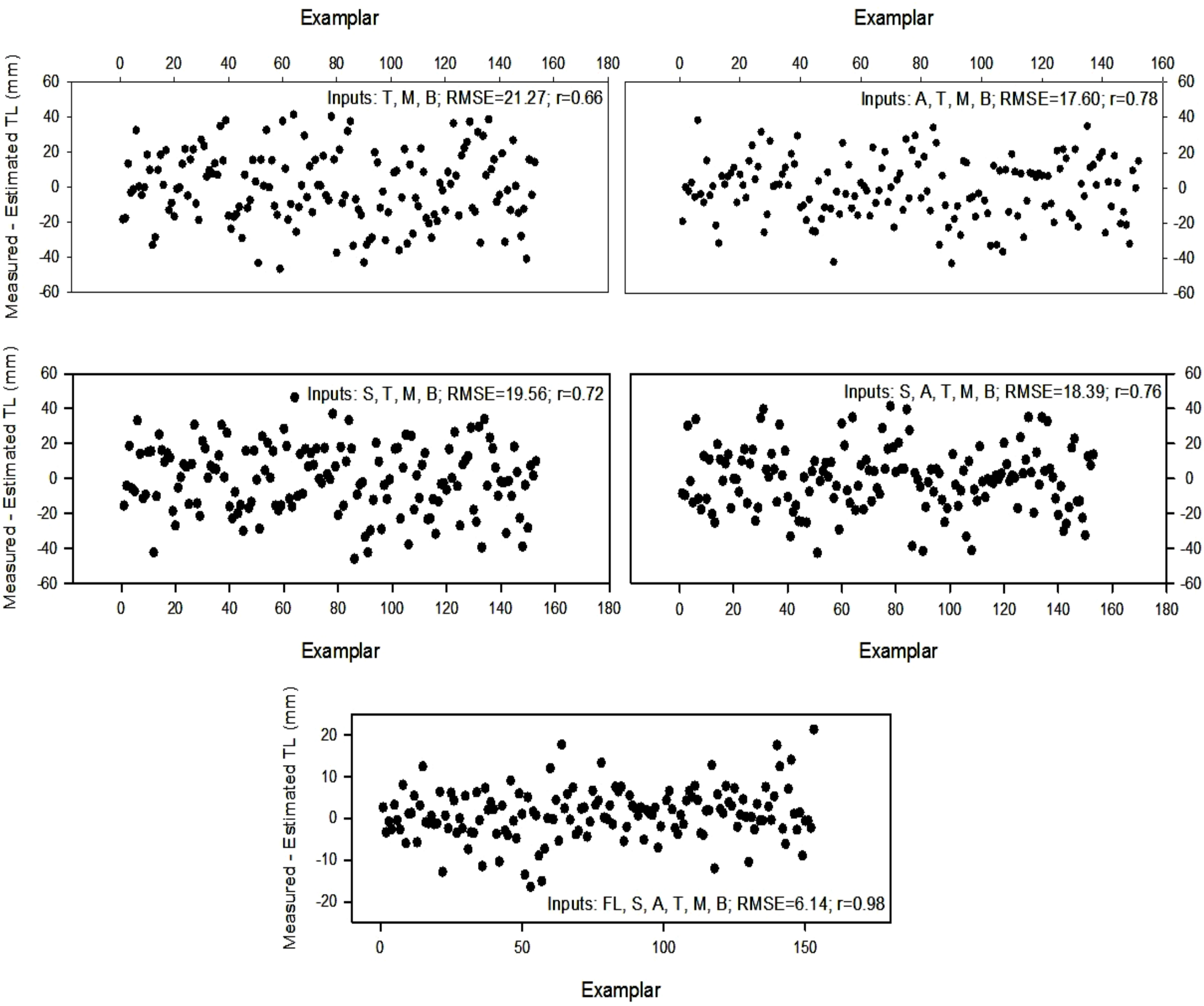

Figure 3. Differences between measured and estimated TL for training data

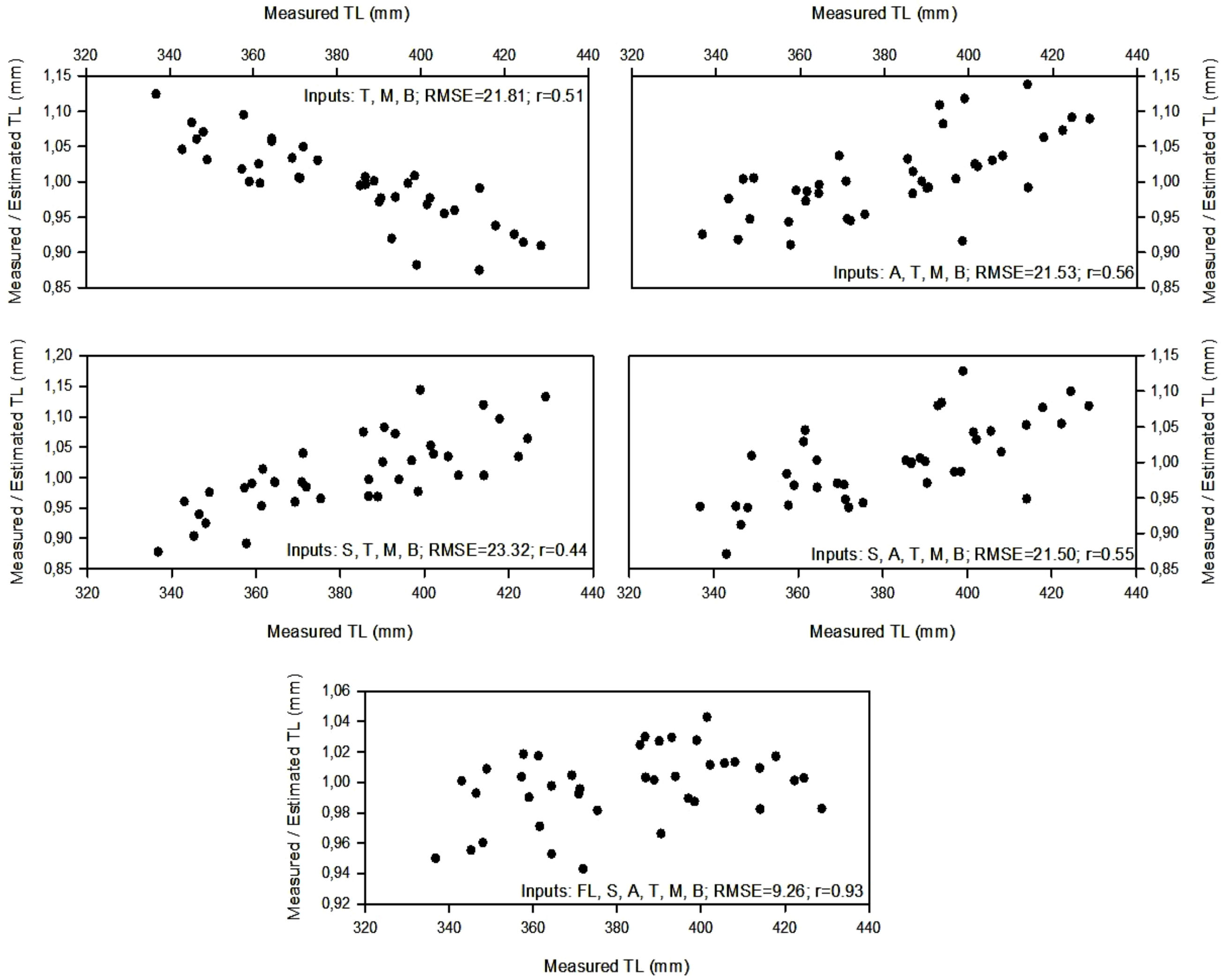

Figure 4. Ratio of measured and estimated TL according to the measured TL for test data

CONCLUSION

In this study, the ANN method was applied for the first time for the estimation of tibia length from proximal tibial transverse diameter. The algorithm used here has the potential to be used in the tibia length estimation in fractures. According to the results, the deviations from actual tibia length were approximately 5%. As the method is reliable, easy to apply, non-invasive and the results are quickly available, this tibia length estimation method can reduce radiation exposure and cost. The biggest problem in the length calculation method from direct AP graph is magnification. Although full AP and films not taken from the appropriate distance were excluded in this study, this problem has been reported in the literature [18].

Conflict of interest

The authors have no conflicts of interest to declare.

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