Estimation of Body Fat via Levenberg – Marquardt Algorithm

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Abstract— The importance of this study is to evaluate the performance of Levenberg - Marquardt neural network in estimating the amount of body fat as an aid for clinical analysis. The aggregate of fat in the human body is interrelated to health and fitness. The body fat is calculated using Levenberg–Marquardt (LM) algorithm using height, weight, Body Mass Index (BMI), age and gender. A sample dataset consisting of two hundred and fifty people between the age group of 20-60 from both genders were taken for analysis. The simulation results were compared with clinical results to test the level of accuracy in finding the body fat. It is found that the results of LM algorithm have a close approximation with the clinical findings.

Key words: Levenberg - Marquardt algorithm, body mass index, body fat

I. INTRODUCTION

The amount of fat in the human body is interrelated to health and fitness. In 2014, more than 1.9 billion adults of 600 million populations were obese [1]. It was found that overweight was prevalent in 18 years and older. The excess in body fat leads to diseases such as cardiovascular diseases (mainly heart disease and stroke), diabetes, blood pressure and cancer (Endometrial, Breast and Colon). It also leads to Osteoarthritis (Hung-Teng Chang et al). The measurement of body fat can be calculated by having Body Mass Index (BMI), Age, Gender, Waist-Hip ratio and so on.

An Artificial Neural Network [ANN] is a reckoning model based on functions and structure of Biological Neural Network. Neural networks are widely used techniques with reserved characteristics which provide exclusive solutions to wide range of disputes. The multiple and interconnecting processing elements implement numerous problems in simple and efficient methodology giving an optimized result. This structure is imbibing of brain processing and its capacities. The structure results into a various mathematical models like feed forward structure and feedback structure. The input, hidden and output elements formulate the problem into a mathematical structure.

Barbosa presented a neural network approach to model body composition by accessing the percentage of body fat through skin fold thickness measurement with caliper devices. The Levenberg-Marquardt algorithm was used to train and test individuals with 60 or more years of age. Heish et al [2008] applied an adaptive linear neural network model to access the body fat of elderly group aged from 60-70 years. Mohammad et al used a two multilayer feed forward neural network model where all independent variables are identified in the literature are included in the former model and the latter one used variables of significance as a result from multiple linear regression. It was concluded latter was better than former. Hang et al used back propagation neural network software – Alyuda Neuro Intelligence for analysis to determine the obesity level. The dietary behavior and living habits were also considered as parameter to determine the body fat.

The Levenberg-Marquardt (LM) algorithm is suitable for small and medium size problems. It provides fast and stable convergence. This paper describes an approach using LM algorithm to access the body fat using height, weight, Body Mass Index (BMI), age and gender. To test this approach data were collected from various physical fitness centers located around local areas. The simulation results were compared with clinical results to test the level of accuracy. It was found that LM algorithm is the fastest training algorithm.

II. BODY MASS INDEX

BMI is universally accepted and scientific method which is used to measure obesity. Bmiis a calculated value which shows the fat content in the human body. If the value of BMI is higher, then that person is affected by Obesity. BMI of a person is calculated using the factors height and weight. BMI value will show whether that particular person is underweight or obese. BMI value is large then the growth of the adipose tissue increases. If the height of a person is in meters and weight in kilograms then the formula can be given as follows

$$B=W/H^2$$

Where B denotes BMI
W denotes weight in kilograms and
H denotes height in meters.

III. BODY FAT

The percentage of body fat is the ratio of total body fat and body weight. The increase in adipose tissue affects the normal function of the body. The fat percentage also measures the fitness level of a person. The percentage of body fat differs depending upon age and gender. The body fat can be calculated from BMI where gender and age is also a parameter. The gender parameters can be given as 0 for female and 1 for male. The calculation of body fat can be stated as follows

$$BF\%=(1.20 \times B)+(0.23\times A)-(10.8 \times G)-5.4$$

Where BF denotes body fat,
B denotes body mass index
A denotes age and
G denotes gender.

IV. LEVENBERG - MARQUARDT ALGORITHM

He Levenberg Marquardt algorithm which is considered as best training algorithm. The algorithm consist of different phases in training. The algorithm part consist of two phases, forward computation and backward computation. In Forward Computation, net value is calculated first and then the output of the processed inputs is calculated. In case of any errors the network uses Backward Computation to adjust the weights and computes until the error rate is minimum. The Diagrammatic representation of a Levenberg-Marquardt back propagation for calculating body fat is given below.

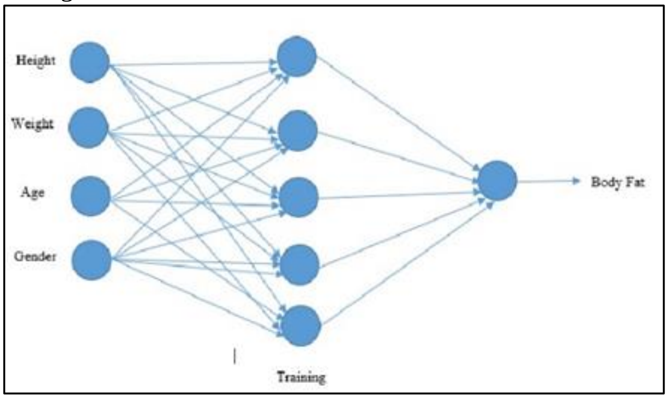

Fig. 1: Calculating Body Fat using Lm Backprobagation

V. METHODOLOGY

The sample dataset consist of Two Hundred And Fifty data of people between the age group of 20-60 in both genders. Each data comprises four parameters. In the above network five hidden elements are tried.The data are assessed using LM algorithm. The network has four neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer. The input neurons have height, weight, age and gender as input values. Then the hidden layer process the input from input layeralong with bias and weight values. Then the output obtained is body fat.

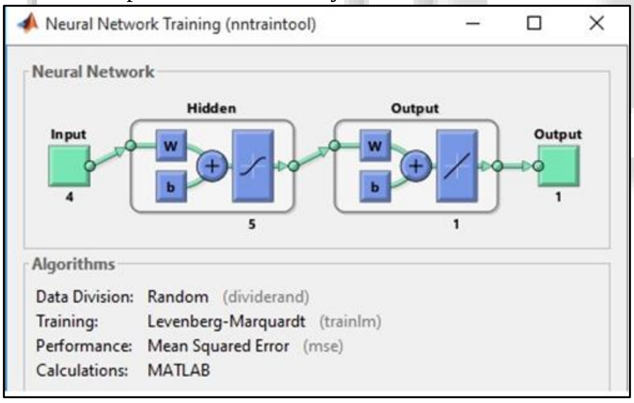

Fig. 2: Screenshot

The Levenberg - Marquardtbackpropagation neural network generated using Matlab 2015a is depicted in Figure 2. The sample data set is shown in the Table 1.

The Levenberg - Marquardtbackpropagation neural network generated using Matlab 2015a is depicted in Figure 2. The sample data set is shown in the Table 1.

Persons	Height (cms)	Weight (kg)	Age	Gender
P1	154.25	67.75	22	1
P2	173.25	72.25	23	0
P3	154	66.15	40	1
P4	184.75	72.15	47	0
P5	184.25	71.25	55	1

Table 1: Sample Input Data

The target for the above data set is given in Table-2. To start the initial training, the weights are selected randomly. The weight and bias are generated using Nguyen-Widrow algorithm where the values have a randomness. Weights are passed to the active neurons. The algorithm trains the data whose target is already known and the process is repeated until approximation value is achieved. By using this method training works faster than other methods. To evaluate the performance of the network Mean Squared Error Function (MSE) is used.

Persons	Target
P1	21.3812
P2	28.8125
P3	26.4852
P4	30.8523
P5	21.6589

Table 2: Sample Target Data

VI. ANALYSIS

Data were analyzed is One-way analysis of variance was used to assess the significance of differences among groups on variables of interest pretest. A two-way (group-by-time) mixed-model analysis of variance and follow-up tests for simple effects were used to determine the significance of differences in daily physical activity, dietary energy intake, and dietary composition. Analysis of variance on change scores was used to assess the significance of differences among groups on body-composition measures (4-component model); Tukey's post hoc analysis was performed if there was a significant finding. Analysis of variance and Tukey's post hoc analysis (among groups within method) and planned comparisons (all clinical estimates compared with %bfd,w,m) were used to determine the significance of differences in %BF pretest and changes in %BF. Individual agreement between clinical estimates of change in %BF and changes in %bfd,w,m was assessed by using the Bland-Altman approach. Relations between variables were described by using simple linear regression analysis. An experiment-wise α level of 0.05 was used. Bonferonni correction was used to control the family-wise error rate (Pfw) when multiple comparisons were conducted.

VII. FUTURE STUDIES

Many questions remain about the metabolic cost and muscular activity required for leg swing in walking. For instance, is leg swing more expensive at faster walking speeds? Are there other combinations of AHF and ESA forces that would further decrease metabolic cost and muscular activity? Could a combination of simulated reduced gravity, horizontal propulsive, anterior leg swing, and bilateral stabilizing forces during walking reduce the net metabolic cost and muscular activity close to zero? Can these assistive devices be useful clinically to help rehabilitate patients with neuromuscular deficits? These questions can be further investigated with the help of forward dynamic computer simulations, guided by the present EMG and GRF data.

VIII. RESULT AND DISCUSSION

Neural network toolbox from Matlab R2015a is used to train the above data set. In this paper LM algorithm trains the given data set by minimizing errors. The LM back propagation algorithm stops the training automatically until the maximum of target is reached. The error is calculated by subtracting the current output with the target value. It is found from the results that the calculated value and the target value differs by a maximum of0.5 and minimum of 0.005, where the above said values are set as minimum and maximum threshold values for error.

IX. Conclusion

This paper a neural network based approach for the discovery of body fat is given as body fat detection is very important, because it leads to many diseases. This paper clearly shows how neural network is used in the clinical analysis in the detection of body fat. This model simply uses the height and weight as initial method for calculating body fat and as future enhancement more parameters can be included to get a better accurate result.

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