

Comparison of Artificial Neural Networks with Logistic Regression for Detection of Obesity

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Abstract Obesity is a common problem in nutrition, both in the developed and developing countries. The aim of this study was to classify obesity by artificial neural networks and logistic regression. This cross-sectional study comprised of 414 healthy military personnel in southern Iran. All subjects completed questionnaires on their socio-economic status and their anthropometric measures were measured by a trained nurse. Classification of obesity was done by artificial neural networks and logistic regression. The mean age \pm SD of participants was 34.4 \pm 7.5 years. A total of 187 (45.2%) were obese. In regard to logistic regression and neural networks the respective values were 80.2% and 81.2% when correctly classified, 80.2 and 79.7 for sensitivity and 81.9 and 83.7 for specificity; while the area under Receiver-Operating Characteristic (ROC) curve were 0.888 and 0.884 and the Kappa statistic were 0.600 and 0.629 for logistic regression and neural networks model respectively. We conclude that the neural networks and logistic regression both were good classifier for obesity detection but they were not significantly different in classification.

Keywords Artificial neural network · Logistic regression · Obesity · Classification

Introduction

The prevalence of obesity has been increasing globally, making it an important health problem both in developed

and developing countries in which it is reaching epidemic proportions [1–6]. According to the World Health Organization in 2005 approximately 1.6 billion adults (age>15) were overweight, at least 400 million adults were obese and at least 20 million children under the age of 5 years were overweight globally. The number of overweight and obese individuals is estimated to reach 2.3 billion and over 700 million persons by 2015 [7].

There are different methods such as dual energy x-ray absorptiometry (DXA), hydrostatic weighing (HW), body mass index (BMI) and bioelectrical impedance analysis (BIA) for classification of persons to obese, overweight or normal weight. Among them DXA and HW are expensive, time consuming, invasive and not used in epidemiology studies, but BMI and BIA are simple, quick, noninvasive and used in epidemiology studies.

Artificial neural networks which were inspired by neurobiology and by the architecture of the human brain are non-parametric pattern recognition techniques that find “hidden patterns” between dependent and independent variables [8].

In recent years, neural networks have gained wide popularity in many disciplines of science and medicine. Neural networks models can learn from examples, incorporate large number of variables, and provide adequate and quick response to new information not previously presented to them.

Neural networks was rarely used to classification obesity. In the previous studies, the factors used for obesity classification with neural networks were clinical factor that are difficult to obtain [9]. In current study, based on anthropometric measures, obesity classification was performed by neural networks and logistic regression and the results of two methods compared with ROC curve.

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Materials and methods

Study design and subjects

This investigation was conducted with a cross-sectional design to determine the prevalence of obesity from February to March 2010 among 465 (51 subjects were excluded because some measurements of them were missed) military personnel in southern Iran. The study was approved by the committee of research ethics in Military Service, and University of Medical Sciences.

Measurements

Demographic and life style information including; age, marital status, level of education, duration of physical activity per week, history of smoking, with its frequency were obtained from each individual. Anthropometric measures including; weight, height, mid-upper arm circumference (MUAC), waist circumference (WC), hip circumference (HC), triceps skinfold and abdomen thicknesses measured by the trained auxologists using techniques presented by Cameron [10]. WC was measured to unit millimeter, as an average of three measurements, by measuring waist diameter at midpoint between iliac crest and lower border of tenth rib. The triceps skinfold and abdomen thicknesses were measured to unit millimeter in triplicate, using a Harpenden caliper device, applying the average of the right and left of subjects. Body weights (measured to the last 10 g) and heights (measured to unit centimeter) were measured using Seca digital scale (Germany) and a non-stretchable wall meter, respectively. Body mass index (BMI) was calculated by weight in kilogram divided by square of height in meter ($\frac{\text{kg}}{\text{m}^2}$). Body Fat Mass (BFM) and body fat percent (%BF) were obtained using BIA method by hand-to-hand Omron BF-500 set, Japan. The cutoff point of obesity according to American College of Sports Medicine is defined as body fat percent > 25% [11]. We asked participants to sit in a silent room for 5 min and afterward we measured the arterial blood pressure from the right arm by a calibrated digital instrument for two times.

Logistic regression

The logistic regression most frequently used to determine the risk of relationships between disease and exposure [12]. Several studies used logistic regression for classification and prediction of the obesity [13–16], where the outcome is a binary variable: the obese or normal. In this case, the probability P of obesity is derived as a function of the following combination of obesity parameters:

$$\log \left[\frac{p}{1-p} \right] = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k$$

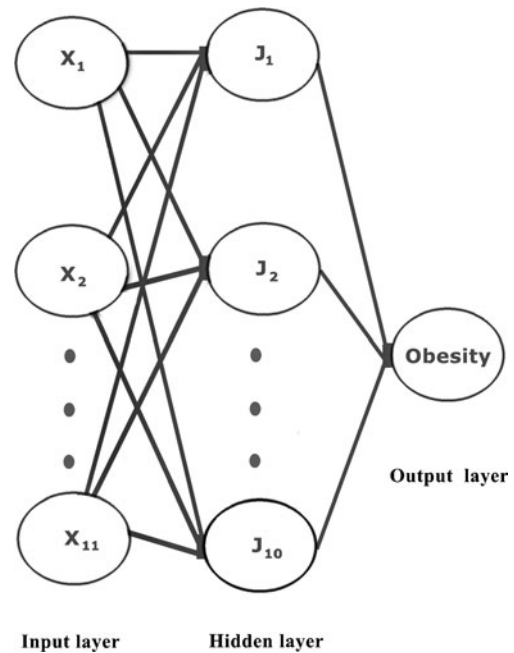


Fig. 1 Neural networks structure

where p is the probability of a binary response, $\beta_0, \beta_1, \dots, \beta_k$ are the coefficients associated with each explanatory variable x_1, x_2, \dots, x_k . A nonzero regression coefficient β_i represents a correlation between the variable x_i and the outcome. The regression coefficients and their standard deviations are calculated using a least-squares fit, and their statistical significance is determined by the P value using the Wald test. If P value less than 0.05, β_i was a nonzero coefficient.

Table 1 Mean±SD anthropometric characteristics based on subject's obesity

	Normal	Obese	P value
Age	33.7±7.7	35.1±7.1	0.061
Systole	116.1±12.0	117.3±11.6	0.276
Diastole	74.5±9.4	77.0±9.4	0.008
Weight (kg)	72.6±9.6	84.9±9.8	<0.001
Height (cm)	172.5±6.4	171.7±5.8	0.204
BMI (kg/m ²)	24.4±2.8	28.8±2.9	<0.001
WC (cm)	83.4±9.0	94.6±8.4	<0.001
MUAC (cm)	28.1±3.2	30.6±3.3	<0.001
Triceps skinfold (mm)	14.5±4.9	18.9±5.9	<0.001
Abdominal (mm)	16.8±6.5	23.6±7.1	<0.001
HC	95.6±6.1	104.5±5.3	<0.001

BMI: body mass index; MUAC: mid-upper arm circumference; WC: waist circumference; HC: hip circumference.

Table 2 Odds ratios and coefficients of binary logistic regression analysis of factors associated with obese

Characteristic	Coefficient	Standard error	Odds	95.0% CI for odds		P value
				Lower	Upper	
Constant	-25.267	3.380	-	-	-	<0.001
Abdominal skinfold	0.052	0.022	1.054	1.009	1.100	0.017
Weight	-0.058	0.027	0.943	0.895	0.995	0.031
HC	0.153	0.043	1.165	1.072	1.267	<0.001
BMI	0.501	0.087	1.650	1.391	1.956	<0.001

HC: hip circumference; BMI: body mass index; CI: confidence interval.

Neural networks

An artificial neural network is a computing system consisting of simple inter-connected processing elements called neurons. The input signals (input data) pass through the network of neurons to generate the network response(s). Each neuron (except the input ones) receives the information from several neurons through connection in proportion to their weights, sums them up and modifies the sum through a non-linear transfer function before passing the signal to other neurons [17].

A Multi-layer perceptron with input layer, hidden layer and output layer was used. The back-propagation algorithm was used for training of the models. A hyperbolic-tangent transfer function was used in all cases.

It is important to adjust learning rate and momentum term during the learning process of the neural networks. High weights may destroy learning behavior of the neural networks. Learning rate set as small value to prevent selection of high weights. Small learning rate slows down the learning process. Learning rate and momentum is set as 0.1 and 0.7 [8].

Input layer consists of 11 neurons corresponding to independent measures (age, systole, diastole, weight, height, BMI, MUAC, WC, HC, triceps skinfold and abdominal thicknesses). Such measures were used to classify participants into two groups (normal and obese). In hidden layer, different number of neurons were used for optimal selection of

networks architecture and preventing over training (Fig. 1). Data was divided into three groups: training (60% of total data), cross-validation (15%) and test (25%) sets. Before training the model input data were normalized. The network was trained in 5000 epochs for different number of neurons in hidden layer. In each epoch training data set was selected randomly to prevent learning especial order of data.

To select the best number of neurons in the hidden layer, the mean squared error (MSE) of training and cross-validation data were computed for different neurons. Minimum of MSE cross-validation is a measure for best number of neuron in hidden layer. Performance evaluation was done by test data.

Neural network and logistic regression analysis were compared by receiver operating characteristic (ROC) curve and Kappa measurement of agreement. The relationship between sensitivity and specificity is exhibited by ROC analysis when a predictive output for two groups is continuous. The area under ROC curve is calculated for performance of the model. The ROC curve was obtained by plotting sensitivity rate against 1-specificity rate for all possible cut-off points. According to the obesity input variables, a cutoff value was selected to classify the normal or obese persons correctly [18].

Descriptive statistics, Kappa measurement of agreement and logistic regression were performed by Statistical Package for Social Sciences (SPSS) version 15. Neural networks was performed by MATLAB software version

Table 3 Number of correct predictive values of obese using logistic regression and neural networks

			True value	
			Normal	Obese
Neural networks	Training	Normal	109	23
		Obese	25	91
	Test	Normal	47	10
		Obese	8	39
	Cross validation	Normal	32	5
		Obese	6	19
Total	Normal	187	38	
	Obese	39	149	
Logistic regression	Total	Normal	186	41
		Obese	41	146

Table 4 Sensitivity, specificity and area under ROC curve using logistic regression and neural networks

	Input variables	Correct classification	Sensitivity	Specificity	Area under Roc curve	Kappa
Logistic regression	Abdominal skinfold, weight, HC, BMI	80.2	80.2 (73.8–85.7)	81.9 (76.3–86.7)	0.888 (0.853–0.917)	0.600
Neural networks	All variables	81.2	79.7 (73.2–85.2)	83.7 (78.2–88.3)	0.884 (0.849–0.913)	0.629

7.8. ROC curve was analyzed by MedCalc statistical software version 8.

Results

Among 465 subjects, 414 (89.0%) of them had complete data. The mean±SD age of participants was 34.4±7.5 years (ranging from 20 to 54 years). A total of 187 (45.2%) had obese. In obese group the mean of diastole, weight, body mass index, mid-upper arm circumference, waist circumference, triceps skinfold thickness, abdominal and hip circumference were significantly more than normal group. But the age, systole and height were similar in two groups (Table 1).

Explanatory variables in logistic regression and neural networks were age, systole, diastole, weight, height, BMI, MUAC, WC, HC, triceps skinfold and abdominal thicknesses. Using binary logistic regression abdominal thickness, weight, BMI, HC were significantly associated with obese, while other explanatory variables were removed from model by backward method (Table 2). The true and predicted status of participant, classified by logistic regression for all subjects showed in Table 3. Logistic regression method correctly classified 80.2% as obese with sensitivity and specificity being 80.2 and 81.9 (Table 4).

The other method for classification of participants in two groups was neural networks. The result of cross validation MSE to select the best network architecture in hidden layer was shown in Fig. 2. The minimum MSE occurred at ten neurons in hidden layer. The network was then selected at 11 neurons in input layer, ten neurons in hidden layer and one neuron in output layer.

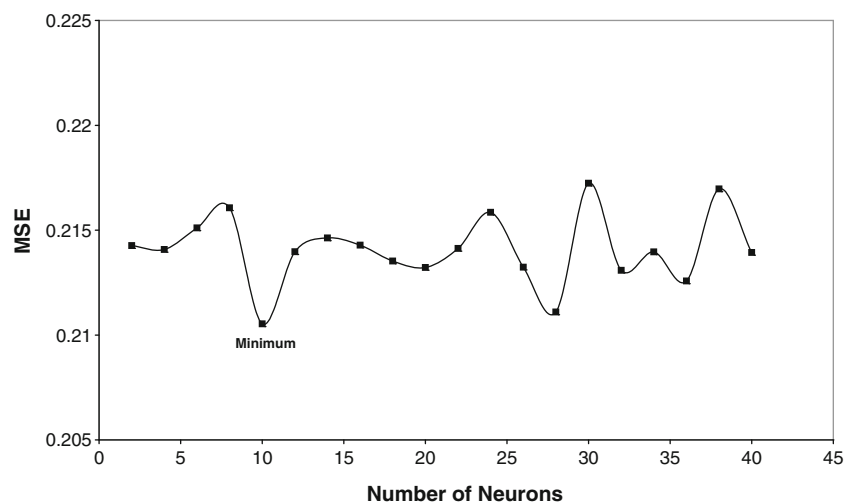
Neural networks correctly classified 80.6% of cases as obese in the training dataset, 82.7% in the testing set, 82.3% in the cross-validation, and 81.2% of all subjects (Table 3). The sensitivity and specificity were 79.7 and 83.7 respectively (Table 4).

The area under ROC curve were 0.888 and 0.884 (Fig. 3) and the kappa statistic were 0.600 and 0.629 for logistic regression and neural networks model respectively, showing that the classification model was not done by chance ($P<0.001$).

Discussion

The popularity of logistic regression may be due to the interpretability of model parameters and being user-friendly. For neural networks, this may be because of the fact that these models may be viewed as nonlinear generalizations of logistic regression, and thus at least as

Fig. 2 Mean square error of cross-validation for different number of neurons in hidden layer



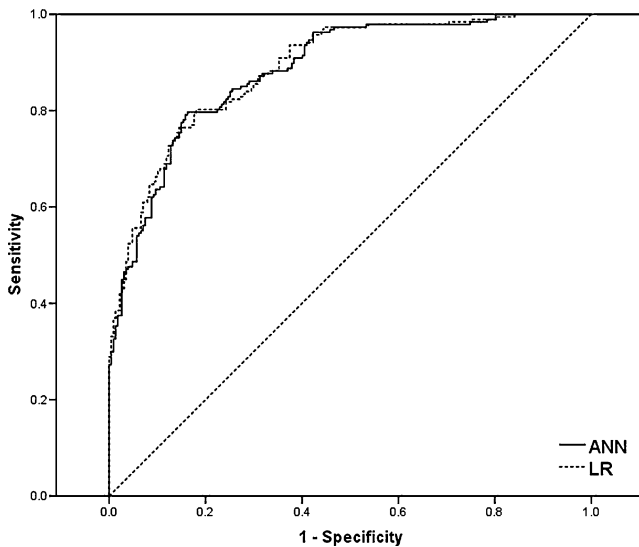


Fig. 3 Receiver-operating characteristic (ROC) curves for Logistic regression (LR) and artificial neural networks (ANN)

powerful as logistic regression [19]. Neural networks is a new method in medicine. This method is rarely used in obesity [20, 21]. For classification, two studies have been performed on obesity [9, 22]. In our study, the obesity was classified by logistic regression and neural networks. In neural networks all 11 measures were entered into input layer for analysis while in logistic regression four influen-

tial variables entered model by backward method. BMI had the highest odds ratio.

The area under ROC curve and Kappa statistic were utilized in order to compare neural networks and logistic regression. In logistic regression and neural networks the area under ROC curve were 0.888 and 0.884 respectively. However the neural network had slightly lower value but it was not significant ($P=0.365$). In a study for classification of obesity disease area under ROC curve for logistic regression and neural networks were 0.902 and 0.923 [9]. The other study for classification of diabetes showed that area under ROC curve were 0.76 and 0.77 for logistic regression and neural networks respectively [23]. These studies showed that the area was not significantly different in two models, then logistic regression and neural networks were similar in classification subjects.

The Kappa value for logistic regression and neural networks were 0.600 and 0.629 respectively. Similar to area under ROC curve, the Kappa statistic for neural networks was barely higher than logistic regression.

The ten ordered groups were created based on their estimated probability with logistic regression and neural networks; those with estimated probability below 0.1 form one group, and so on, up to those with probability 0.9 to 1.0. Each of these categories is further divided into two groups based on the actual obesity status.

Table 5 Deciles of risk base on logistic regression and neural networks

		True value		Total
		Normal	Obese	
Logistic regression	Decile 1	91 (95.8)	4 (4.2)	95
	Decile 2	42 (85.7)	7 (14.3)	49
	Decile 3	14 (41.7)	10 (41.7)	24
	Decile 4	22 (64.7)	12 (35.3)	34
	Decile 5	18 (69.2)	8 (30.8)	26
	Decile 6	12 (48.0)	13 (52.0)	25
	Decile 7	13 (32.5)	27 (67.5)	40
	Decile 8	8 (26.7)	22 (73.3)	30
	Decile 9	6 (19.4)	25 (80.6)	31
	Decile 10	1 (1.7)	59 (98.3)	60
Artificial neural networks	Decile 1	96 (96.0)	4 (4.0)	100
	Decile 2	30 (90.9)	3 (9.1)	33
	Decile 3	23 (60.5)	15 (39.5)	38
	Decile 4	21 (70.0)	9 (30.0)	30
	Decile 5	18 (72.0)	7 (28.0)	25
	Decile 6	10 (33.3)	20 (66.7)	30
	Decile 7	12 (34.3)	23 (65.7)	35
	Decile 8	11 (28.9)	27 (71.1)	38
	Decile 9	4 (16.0)	21 (84.0)	25
	Decile 10	2 (3.3)	58 (96.7)	60

Logistic regression and neural networks were almost similarly correctly classified participants to obese and normal in the first, second, 9th and 10th deciles, but both did not have good performances in 3rd, 4th, 5th, 6th, 7th deciles (Table 5). This stated that the problem was mainly in boundary condition with crisp decision.

In neural networks the relation between input and output factors due to network complexity are not clear. Neural networks are black box model. Hart and Wyatt argued that this “black box” aspect is the major barrier to the acceptance of neural networks for medical decision systems [24]. Several researches in medical diagnosis have shown that neural networks have almost similar result in classification in comparison to logistic regression [9, 23, 25]. Analysis of 72 papers compared neural networks and logistic regression in medicine indicated that neural networks in half of the studies did not outperform the logistic regression [19].

Neural networks and logistic regression were compared for childhood obesity prediction. The results showed the neural networks had better performance than logistic regression [26]. Bourdès et al. showed the neural networks predicted breast cancer better than logistic regression [27]. Also Shadabi et al. compared artificial neural networks with logistic regression in prediction of kidney transplant outcomes and concluded the neural networks was better predictor [28].

We conclude that the neural networks and logistic regression both were good classifier for obesity detection but they were not significantly different in classification. Further researches on neural networks training are suggested to customize it for obesity classification.

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