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Original Article

Diagnosis and Prediction of Obesity and Its Effective Factors Using Artificial Neural Network: A Case Study of Children and Adolescents Residing in Isfahan-Iran

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Abstract

Introduction: Overweight obesity is now so widespread in the world. This study aims to use an artificial neural network modeling tool to develop a predictive model for the diagnosis of obesity in children and adolescents.

Methods: Participants consisted of 460 school students, aged 7-18 years, who studied in a national school-based surveillance program (CASPIAN-V). Training network with 10 input variables including: age, sex, weight, height, waist circumference, systolic blood pressure, diastolic blood pressure, body mass index, waist-to-height ratio, physical activity, and with output variable obesity with 17 and 15 hidden neurons for girls and boys was designed.

Results: After designing the network, the value of gradient on the data was 0.0021194 for girls and 0.0031658 for boys. The sensitivity, specificity and accuracy of the neural network were 0.9444, 0.9855, 0.9822, respectively in girls, and 0.9655, 0.9757, 0.9755 in boys; in all these cases, the designed artificial neural network performed better than waist circumference and body mass index. A review of the final weights of this network showed that the input variable body mass index in girls and the input variable waist-to-height ratio in boys had the most influence in diagnosis of obesity.

Conclusion: Our results show that although body mass index has a better diagnostic performance in determining excess body fat than waist circumference, in boys and girls of both groups, and also in all parameters of sensitivity, specificity and accuracy, the artificial neural network acts better than body mass index and waist circumference, so that with an accuracy of more than 96%, we can detects obesity.

Keywords: Artificial neural network, Body mass index, Waist circumference, Obesit.

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Introduction

The outbreak of non-communicable diseases is increasing rapidly worldwide. Especially in advanced societies, non-communicable diseases are estimated to make up 75% of the global mortality rate in low- and middle-income countries (1). One of the most common metabolic disorders that can lead to many non-communicable diseases such as cardiovascular disease, diabetes, some cancers, kidney disease, and mental illness is metabolic syndrome. Previous studies have shown that abdominal and general obesity, weight disorders, dietary factors, and sedentary lifestyle are all risk factors for metabolic syndrome (2, 3). The concept of metabolic syndrome over the last few decades has been dependent on a variety of factors including the genetic environment, epidemiological transmission, sedentary lifestyle, and escalating trend of childhood obesity (4, 5). Baygi et al. showed that obesity was associated with high birth weight children and the age at onset of supplemental feeding. Also, interventions are needed to reduce the prevalence of obesity (6). Increasing the prevalence of obesity is one of the important factors in increasing insulin levels in children, and taking preventive measures to improve the quality of life of children who are the productive force of society tomorrow is of great importance (7).

Obesity is replacing malnutrition and infectious diseases as the most important cause of disease and is determined by body mass index (BMI) higher than 30 kg/m^2 (8). Of course, this number is different for different age groups and regions (9, 10). Since metabolic syndrome involves the person from childhood to adulthood, and people with metabolic syndrome are at higher risk for coronary heart diseases and other fatty plaque-forming diseases on the arterial wall, such as stroke and artery diseases, so early diagnosis of this disease increases the chance of successful treatment of the patient (11). Overweight and obesity are the abnormal accumulation of fat in the body that damages human health. In children and adolescents, BMI is used to measure overweight and obesity (12). BMI is defined as a person's weight in kilograms divided by the square of height in meters (kg/m^2). Despite the fact that BMI is easy to apply in an epidemiological data and clinical setting, and although it has showed an association between increased BMI and cardiovascular events (12), BMI fails to distinguish between the fat mass and lean body mass (13). Therefore, it seems that BMI is a poor predictor for excess body fat.

There are some other anthropometric measurement tools to detect excess body fat in literature. For example, skinfold thickness, waist circumference (WC), and waist-to-height ratio (WHtR) can be mentioned. Skinfold thickness is often suggested as the best predictor of excess body fat percentage in children (14, 15), but the measurement requires more effort (time and technical, caliper is needed) than determination of the BMI or the WC and is, thus less often used clinically.

Recently, many studies have used artificial intelligence tools, especially artificial neural networks (ANNs), to diagnose and predict diseases in the medical field (16-22).

The high capacity of ANNs inspired by biological computational networks has led to their rapid expansion. Also, some attempts to predict excess body fat percentage in adults by ANNs approach have been reported (23-25).

The literature review indicates the high number of studies using ANN tools in the prediction and classification of multiple diseases, which will be briefly mentioned.

Using an ANN-based diagnostic model for heart disease and using a set of its common genetic factors, including clinical, laboratory, operative, angiographic, and single nucleotide polymorphisms of 487 patients, Atkov et al. showed that the back propagation multilayer perceptron network, accurately detected 64% to 94% of the disease. These researchers improved the accuracy of the models using a genetic algorithm with various optimization parameters including the number of neurons in the hidden layer, number of network inputs, and the slope of activity functions. Similar to the results of the present study, recent researchers have shown that although the use of all the factors makes the model complex, the use of fewer factors does not provide vital information (16). Kuduvalli et al. in a mortality study of obese patients after open heart surgery in hospital, using logistic regression method, showed that excessive obesity had a significant relationship with atrial arrhythmia and chest ulcer infections, and people with severe obesity (with BMI greater than 35) are 4.17 times more likely to be infected. However, these researchers found that obese patients were not at increased risk of death after open heart surgery in the hospital (17). In a study of the association between excessive obesity and mortality in patients with heart failure, Horwich et al. showed that four groups of patients with BMI less than 27 (as weight loss) up to 31 (as excessive obese) had similar survival rates, but overweight and obese groups showed higher rates of hypertension and diabetes, and higher levels of cholesterol, triglycerides and LDL cholesterol (18). In Valavanis et al.'s study of the pathology of obesity, its association with cardiovascular disease and the identification of genetic variation using ANN, it was shown that the network developed by genetic algorithm with the accuracy of 61.46%, gives the best fits to the data (19). Liu et al. used ANN models to predict cardiovascular failure in the general Chinese population and based on data from 2092 individuals between the ages of 30 and 80 years, ANN was an effective tool in predicting these problems in China. The model used by them included 14 neurons in the input layer, 18 neurons in the hidden layer, and one output neuron (20). Tang et al. evaluated an identical efficacy for both ANN and logistic regression models in predicting cardiovascular failure (21). Mohammadpour et al. used an ANN to evaluate whether or not coronary arteries were closed to reduce complications and angiographic injuries in patients who did not require this procedure (22).

In another study, Ergün compared neural network method and logistic regression in the diagnosis of obesity in about 82 people, and finally it was found that the ANN method performed better than logistic regression in the diagnosis of obesity (26). Heidari et al. in a study on 414 people with a mean age of 34 years showed that the neural network with an accuracy of 81.2% and the logistic regression model with 80.2% diagnoses the obesity (27). Using artificial intelligence tools, Duran et al. predicted obesity in children aged 8-19 years (12).

The aim of this study was to design an ANN, so that it can diagnose and predict obesity in 18-7-year-old students with a higher number of input variables and higher accuracy than previous studies. We also aimed to use more parameters, more important and more effective, as well as to achieve higher accuracy in predicting obesity in children and adolescents using ANN tools.

Materials and Methods

ANN is a non-parametric classification method that classifies individuals into patients or healthy individuals based on input variables in the medical field. Classification and prediction of patient status based on risk factors is one of the applications of ANNs (28).

ANN approaches are commonly used to address complex, linear, and nonlinear relations. An ANN is able to recognize the patterns between the input and output data in order to predict the output for unknown input data (29). Figure1 shows a mathematical neuron:

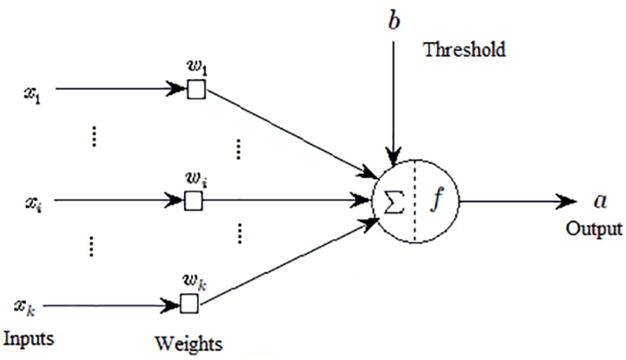

Figure 1: The mathematical neuron

The ANN is inspired by the tangled and massive structure of the human brain. Billions of nerve cells (neurons) through the interconnections they have (synapses) form a biological neural network in the human brain that is dedicated to human activities including reading, understanding, communicating, breathing, moving, recognizing the voice and face, solving the issues, storing the data, and so on. The ANN actually simulates part of the brain's function (30). The mathematical equations of a neuron in the neural network are as follows

$$a = f(n) = f\left(\sum_{j=1}^{k} w_j x_j + b\right) \quad (1)$$

A neuron receives k signals x_1, x_2, … x_k as inputs, multiplying each of them by the corresponding weight numbers w_1, w_2, … w_k and then accumulates the result by a number such as b, named as bias, and forms the net input of n.

Finally, a function such as f (n), called the transfer function, effects on n, and the neuron output, named as a, is achieved. The transfer function is specified according to the type of expected outputs, and neurons can use different transfer functions to generate output. The most common of these functions can be the binary sigmoid and bipolar sigmoid transfer functions (31, 32):

$$f_1(n) = \frac{1}{1+e^{-n}} \quad (2)$$

$$f_2(n) = \frac{1-e^{-n}}{1+e^{-n}} \quad (3)$$

Neural network design has two main aspects of architecture and learning algorithm:

1. Architecture: The neural network has a multilayer perceptron structure (MLP) that often performs better than other methods (33, 34). The MLP structure is a standard combination of inputs, linear and/or nonlinear neural units and outputs and is shown as *NN* $(r\text{-}S_1\text{-}S_2)$ where r is the number of inputs, S_1 is the number of hidden layer neurons and S_1 is the number of output layer neurons.

2. Learning Algorithm: Neural networks have the ability to learn from the past, experience, and the environment while learning to improve their behavior. The neural network uses a supervised learning method for training. In a supervisory learning process, a set of data pairs A=(x_i, t_i), called training samples, is given, where X_i, is the input and t_i is the target output of the network. After applying input X_i to the neural network, the actual output of the network, a_i is compared with t_i and then the learning error is obtained from the relation $e_{i=} t_{i-} a_i$. The resulting error is used to adjust the network parameters, so that if at the next step, the same input X_i is applied to the network, the network output will be closer to t_i.

By having the error value, weights are corrected and the weight correction operation is repeated until the error value of the network reaches the acceptable level.

$$w_{ij}(k+1) = w_{ij}(k) + \eta . x_i(k) . e_i(k) \quad (4)$$

Where η is a positive constant value less than one that determines the learning rate.

The learning algorithm used in the MLP neural network is the error back propagation learning algorithm (EBPL). In the EBPL algorithm, there are two computational paths: the forward path, in which the stimulus functions operate on each of the neurons, and the reverse path, in which the sensing vectors (error vectors) are returned from the last

Table 1: Status of the input and output data*

	Female	Male	All
N	225	235	460
Age (year)	11.8 (3.24)	13.05 (2.87)	12.44 (3.118)
Sex	0 (0)	1 (0)	0.51 (0.5)
Weight (kg)	37.73 (14.59)	45.87 (16.68)	41.89 (16.19)
Height (cm)	142.87 (14.51)	152.68 (16.7)	147.89 (16.41)
WC (cm)	65.55 (9.46)	69.66 (11.86)	67.65 (10.94)
Systolic blood pressure (mm Hg)	98.39 (1.82)	102.62 (11.72)	100.55 (12.95)
Diastolic blood pressure (mm Hg)	63.8 (10.89)	66.21 (9.82)	65.03 (10.42)
BMI (kg/m^2)	17.87 (4.25)	19.10 (4.44)	18.50 (4.39)
WHtR	0.46 (0.51)	0.46 (0.66)	0.46 (0.59)
Physical activity (Days a week)	3.23 (1.34)	2.84 (1.39)	3.03 (1.38)
Obesity (yes, no)	0.09 (0.29)	0.14 (0.35)	0.12 (0.32)

*Data are presented as mean (Standard Deviation) and count

layer to the first layer. Finally, using the information obtained from the above two paths, weights and bias matrices of the MLP grid are adjusted. The mean squared error index can be used to stop the iterations of the EBPL algorithm (35, 36).

This is a predictive study that predicts obesity status in children and adolescents based on input variables and examines them by designing an ANN. The statistical population consists of 460 students living in Isfahan, Iran, aged 7-18 years who participated in the fifth study of adolescent and children non-communicable diseases monitoring and prevention program during the year 2015 in Iran. A questionnaire containing their information about age, sex, weight, height, WC, systolic blood pressure, diastolic blood pressure, BMI, WHtR, physical activity, and obesity was completed by a specialist physician and team after the examination. Motlagh et al. Have provided the full details of the fifth study of the program for monitoring and preventing non-communicable diseases in children and adolescents, which was conducted in Iran during the years 2014-2015 (37). All input and output data have been normalized to reduce the error and have the ANN training process with good convergence. Table 1 shows the general status of the input and output data by gender. Due to the fact that factors such as age, height, weight and WC are effective in obesity (12, 38), in this article, we considered obesity as the output variable of the designed neural network.

Javed et al. showed that excess body fat in children and adolescents diagnosis performance was different with BMI in both genders (39). Our study in preliminary design and review shows the same results, so we designed two different neural networks using the artificial intelligence network toolkit in MATLAB for both genders. About 80% of the data, 178 girls and 188 boys, were used to train the ANN. After implementing multilayer perceptron) MLP) neural network using resilient back propagation (RP) learning algorithm and changing the number of layers and neurons of the network and observing its error, the best structure for girls was obtained NN (10-17-1); for boys, we obtained NN (10-15-1). Finally,

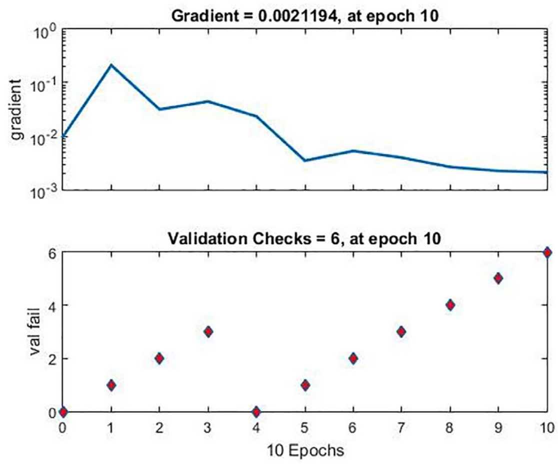

Figure 2: The amount of ANN gradient designed for girls

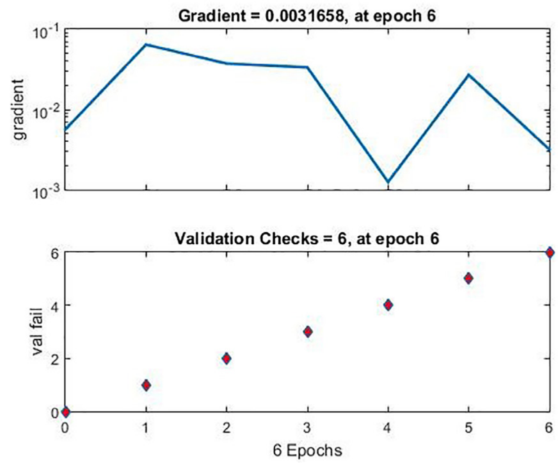

Figure 3: The amount of ANN gradient designed for boys.

Table 2: Results of artificial neural network (ANN), artificial neural network (WC), body mass index (BMI) in the diagnosis of obesity in children and adolescents

Diagnostic parameter	BMI	WC	ANN
Female			
Sensitivity	0.7647	0.5555	0.9444
Specificity	0.9660	0.9512	0.9855
Accuracy	0.9506	0.9192	0.9822
Male			
Sensitivity	0.8235	0.4762	0.9655
Specificity	0.9128	0.9326	0.9757
Accuracy	0.9063	0.8511	0.9745

using the remaining 20% of the patients as the test data, which comprised about 45 girls and 47 boys, the network process was applied to them, and the amount of output was evaluated.

Results

In this study, the amount of gradient (one of the methods to reduce the error in the network is to use the amount of gradient or slope (40)) in the neural network designed for girls was 0.0021194 (Figure 2).

Also, the value of the gradient in the grid designed for boys is 0.0031658 (Figure 3).

Diagnostic Performance of Obesity Using ANN Methods, BMI and WC

Table 2 shows the performance diagnosis of obesity using neural network methods, BMI and WC for both genders. According to Table 2, in girls' groups, the sensitivity, specificity, and accuracy of diagnostic method for the obesity, with WC were lower than BMI method, and these three parameters in the diagnosis of obesity with a neural network were higher than BMI.

In Table 2, the sensitivity and accuracy of the diagnosis of obesity method with WC was lower than the BMI in boys. However, specificity in the WC was higher than the BMI. All three parameters of sensitivity, specificity, and accuracy in the neural network method were greater than BMI and WC.

Discussion

In this study, we evaluated the diagnostic performance of overweight and obesity using ANN methods, BMI and WC. The neural network was designed using the information of 460 students living in Isfahan - Iran aged 7-18 years who participated in the fifth study of non-communicable diseases monitoring and prevention program, including ten input variables (age, sex, weight, height, WC, systolic blood pressure, diastolic blood pressure, BMI, WHtR, amount of physical activity (and an obesity output variable. According to Table 2, in both children and adolescent groups (boys and girls), the sensitivity level, specificity, and accuracy of diagnostic method for the obesity using ANNs were higher than BMI and WC. The specificity value obtained in WC was higher the BMI and lower than the ANN. Our results show that WC has less sensitivity to predict excess body fat in children and adolescents than the other two methods. The reported sensitivity by Wohlfahrt et al., for both genders is 0.592 (41). According to the results in Table 2, out of every 100 boys with obesity, 47 with WC, 82 with BMI, and 96 with the ANNs were correctly diagnosed as obese. Therefore, the ANN method for identifying obesity performs better than WC, and BMI in boys and girls. In Figures 2 and 3, the amount of neural network gradient designed in both numerical genders is close to zero, and this shows that the designed neural network has achieved high accuracy.

Duran et al. for the diagnosis and prediction of obesity in children and adolescents used the ANNs with 4 input variables such as age, height, weight and WC which achieved an accuracy of over 92% (12). While we have 10 input parameters (age, sex, weight, height, WC, systolic blood pressure, diastolic blood pressure, BMI, WHtR, amount of physical activity), we were able to design an ANN with high accuracy of 96% to diagnosis and prediction of obesity in children and adolescents.

This shows that whatever more useful factors are used in determining obesity, diagnosis and prediction are far more accurate. Since we have used ten significant variables in obesity in this study, while this was not the case in previous studies, and they have used fewer variables, much better results were obtained. Although the use of useful variables makes the task more complicated, it will not be complicated with smart tools such as an ANNs.

The final weights obtained after ANN design for girls, with ten input variables, one output variable and 17 neurons in the hidden layer, and for boys, with ten input variables, one output variable and 15 neurons in the hidden layer, showed that the input variable "BMI" in girls and "WHtR" in boys had the most impact on the diagnosis of obesity, and this finding is similar to the results of Flegal et al.'s study on adults over 20 years old participating in the National Nutrition and Health Plan from 1999 to 2004 (42) and those of a study by Choi et al. on 3057 children and adolescents aged 10 to 19 who participated in the fifth Korean National Health and Nutrition Examination (43).

Regarding the neural network weights, the systolic blood pressure input variable for girls and the age input variable for boys have the least effect on the diagnosis of obesity.

Conclusion

Our results show that although BMI has a better diagnostic performance in determining obesity than WC in children and adolescents, in both children and adolescents' groups and also in all parameters of sensitivity, specificity and accuracy, the ANN acts better than BMI and WC. Therefore, the designed ANN provides excellent results for specialist physicians to diagnose and predict children and adolescents' obesity. In this study, a machine learning algorithm was used. In future studies, algorithms and other methods can be used to identify the best algorithm and design a decision support system.

Conflict of Interest: None declared.

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