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Original article

An artificial neural network to predict resting energy expenditure in obesity

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SUMMARY

Background & aims: The resting energy expenditure (REE) determination is important in nutrition for adequate dietary prescription. The gold standard i.e. indirect calorimetry is not available in clinical settings. Thus, several predictive equations have been developed, but they lack of accuracy in subjects with extreme weight including obese populations. Artificial neural networks (ANN) are useful predictive tools in the area of artificial intelligence, used in numerous clinical fields. The aim of this study was to determine the relevance of ANN in predicting REE in obesity.
Methods: A Multi-Layer Perceptron (MLP) feed-forward neural network with a back propagation algorithm was created and cross-validated in a cohort of 565 obese subjects (BMI within 30–50 kg m^{-2}) with weight, height, sex and age as clinical inputs and REE measured by indirect calorimetry as output. The predictive performances of ANN were compared to those of 23 predictive REE equations in the training set and in two independent sets of 100 and 237 obese subjects for external validation.
Results: Among the 23 established prediction equations for REE evaluated, the Harris & Benedict equations recalculated by Roza were the most accurate for the obese population, followed by the USA DRI, Müller and the original Harris & Benedict equations. The final 5-fold cross-validated three-layer 4-3-1 feed-forward back propagation ANN model developed in that study improved precision and accuracy of REE prediction over linear equations (precision = 68.1%, MAPE = 8.6% and RMSPE = 210 kcal/d), independently from BMI subgroups within 30–50 kg m^{-2}. External validation confirmed the better predictive performances of ANN model (precision = 73% and 65%, MAPE = 7.7% and 8.6%, RMSPE = 187 kcal/d and 200 kcal/d in the 2 independent datasets) for the prediction of REE in obese subjects.
Conclusions: We developed and validated an ANN model for the prediction of REE in obese subjects that is more precise and accurate than established REE predictive equations independent from BMI subgroups. For convenient use in clinical settings, we provide a simple ANN-REE calculator available at: https://www.crnh-rhone-alpes.fr/fr/ANN-REE-Calculator.

1. Introduction

Obesity is a serious global public health concern. The benefit of moderate weight loss is clearly demonstrated. An accurate assessment of energy needs is necessary to propose adequate dietary intake [1]. Resting energy expenditure (REE) is by far the largest single component of total daily caloric expenditure. It contributes from 50 to 75% of total energy expenditure, depending of physical

Abbreviations: ANN, artificial neuronal network; FFM, fat-free mass; MAPE, mean absolute percentage error; PP, predictive precision; MLP, multi-layer perceptron; REE, resting energy expenditure; RMSPE, root mean squared prediction error; USA DRI, USA dietary reference intakes.

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activity level [2]. Indirect calorimetry (IC) is commonly accepted as the gold standard for measuring REE. Its availability, the cost of the equipment and the need of trained staff limits the routine clinical use of this method.

Alternatively, predictive equations, usually based on regression analysis of body weight, height, age and sex, have been developed to estimate REE in clinical settings. The reference populations used to generate these equations included only a very limited, if any, number of obese and especially severely obese subjects. Several studies have assessed the validity of REE predictive equations in obese subjects with some controversial results [3–6]. The low accuracy of some predictive equations may lead to underestimation or overestimation of energy needs and contributes to inadequacy in dietary prescription [7]. Some predictive equations take into account body composition and require quantifications of fat free mass (FFM) which is one important determinant of REE. Yet, several studies demonstrated that including body composition data does not improve the accuracy of REE predictive equations in obese populations [5,7–9]. It can be explained by the difficulty to measure body composition especially in obese population [10]. The systematic review of REE equations in obese populations did not support the use of a single prediction equation [11]. It supports the notion that specific REE prediction equations cannot simply be transferred from one population to another although it is widely done in current practice [7].

Artificial neural network (ANN) is an area of artificial intelligence technology and a mathematical system which mimic biological neural networks [12]. ANNs are flexible nonlinear mathematical systems capable of modeling complex functions. They are applicable whenever there is a relationship between independent predictor variables (inputs) and dependent predicted variables (outputs), even though the relationship is composite, multidimensional and nonlinear. ANN takes known data, i.e. previously solved examples, recognizes complex patterns between inputs and outputs and then applies this knowledge on unknown data. The hidden relationships between inputs and outputs are learned and subsequently ANN is able to predict output from the given input of new data [13]. Once appropriate training is performed, the neural networks attempt to predict with a higher accuracy than conventional classification or regression analysis. Due to the ability to detect complex nonlinear relationships between predictors and diseases, ANN has been successfully used in medical decision support systems [13].

The aim of the present cross-sectional study was to develop of an ANN model based on anthropometric parameters for the prediction of REE in obesity. We compared ANN model to established REE prediction equations. We intended to provide an instrument of clinical value in the primary nutritional care of the obese population.

2. Materials and methods

2.1. Subjects

In this cross sectional study, data were collected from a population of 853 obese patients (BMI $\geq$ 30 kg/m^{-2}) consecutively hospitalized for initiation of obesity care management in the Department of Endocrinology, Diabetology and Nutrition of the Lyon Sud Hospital (Lyon, France) between 2010 and 2012. We excluded subjects with a BMI $\geq$ 50 kg/m^{-2} (n = 78), a medical history of bariatric surgery (n = 63), pulmonary hypertension (n = 2), renal or heart failure (n = 19), thyroid disease (included if treated and thyroid function indices within the normal limits), recent neoplasia disease or chronic high-grade inflammatory diseases (n = 2), or type 1 or uncontrolled type 2 diabetes mellitus (n = 12). Subjects using corticosteroids, testosterone, or anabolic agents were excluded (n = 3). From the remaining data set of 674 subjects, we excluded 109 patients whose indirect calorimetric measurements were of unsatisfactory quality: Respiratory Quotient (RQ) < 0.65 or >1, coefficient of variation (CV) of VO2, VCO2 or RQ > 10%. A final data set of 565 obese subjects was used for the analysis. Characteristics of the whole study population and of BMI subgroups 30–35, 35–40, 40–45 and 45–50 are presented in Table 1.

2.2. Indirect calorimetry and anthropometric measurements

The indirect calorimetry measurements were routinely performed with QUARK RMR™ (Cosmed, Rome, Italy), an open-circuit calorimeter using the canopy dilution technique [14]. Ventilatory rate was regulated directly by the system. Calibration of the flowmeter was performed daily using a certified 3 L calibration syringe. The calorimeter was also calibrated daily with a standard gas (5% CO_2, 16% O_2, balanced for nitrogen, Scott Gas, USA for QUARK RMR). The O_2 analyzer is a paramagnetic sensor that has a measuring range from 0 to 30% and an accuracy of 0.02%. The CO_2 analyzer is an infrared digital sensor that has a measuring range from 0 to 10% and an accuracy of 0.02%. For measurement, the subjects had fasted overnight and were in a supine position at complete physical rest. Subjects were asked to remain relaxed but awake and to avoid coughing, talking or moving during the entire measurement period. The ambient temperature was adjusted to maintain thermoneutrality. A default value of 13 g was entered into the system to account for nitrogen excretion. Respiratory gas exchanges were monitored for 30 min. Steady state ventilation was achieved, when the average changes of oxygen consumption per minute (VO2) and carbon dioxide production per minute (VCO2) were less than 10%. This was achieved in approximately 5 min in all cases. The data obtained during the initial 5-min period were discarded and measurements during the remainder 25 min were averaged and used for the calculation of oxygen consumption (VO2) and carbon dioxide production (VCO2). The modified Weir equation $REE = [3.941 \times VO2 + 1.11 \times VCO2] \times 1.44$, was used to calculate energy equivalency from the oxygen consumption and the carbon dioxide production. The respiratory quotient (RQ) was calculated as $RQ = VCO2/VO2$.

Both weight and height were measured under standardized conditions, in the morning, after a fasting period of 12 h, in light clothes without shoes. Height was measured to the nearest 0.5 cm by a wall-mounted stadiometer (SECA 216, SECA GmbH & Co, Hamburg, Germany). Body weight was measured within 0.1 kg with a calibrated electronic flat scale (SOEHNLE Professional GmbH & Co, Germany).

2.3. REE predictive equations

The predictive equations for REE used in our study were obtained by screening previous publications and summarized in Table 2 [11]. We selected 23 available REE predictive equations based on the following criteria: equations based on body weight, height, age, gender; developed in adults; applicable for both sexes. For each subject, we calculated the REE using the selected equations in kcal/d and compared them to the measured REE using indirect calorimetry. For each equation, the REE was calculated with the measured body weight and height at the time of the indirect calorimetry assessment.

2.4. Artificial neural network modeling

The ANN model used in this study was a Multi-Layer Perceptron (MLP), a feed-forward neural network with a back propagation