ARTIFICIAL NEURAL NETWORK APPROACH FOR OBESITY-HYPERTENSION CLASSIFICATION

Octavian Postolache[1], Joaquim Mendes[2]
[1] Instituto de Telecomunicações, Av. Rovisco Pais, 1049-001, Lisboa, Portugal

[2] IDMEC, Faculdade de Engenharia UP, Portugal

Gabriela Postolache[3], Pedro Silva Girão[4]
[3] Universidade Atlantica, Escola de Saude, Oeiras, Portugal

[4] Instituto de Telecomunicações, Av. Rovisco Pais, 1049-001, Lisboa, Portugal

Keywords: Obesity-hypertension syndrome, Artificial neural network.

Abstract: One of the newest targets of public health is management of obesity-hypertension. In this paper is presented the use of an artificial neural network based model for objective classification of obesity-hypertension. Different neural network architectures as part of hybrid processing scheme including comparators and competitive processing blocks were developed and tested. The neural network functionality is the classification of the individuals according to the obesity risks. The results show that the neural network classifier is consistent with the standard criteria suggested by the obesity and hypertension guidelines.

1 INTRODUCTION

Obesity is rapidly turning into an "epidemic" afflicting much of the industrialized world. Obesity is a major risk factor for serious non-communicable diseases such as cardiovascular disease, hypertension, stroke, diabetes mellitus and various forms of cancer. Therefore, it will be one of the major causes of death, according to the estimation of the World Health Organization, which suggest that by 2025 approximately 60% of deaths worldwide will be caused by circulatory diseases and cancers (WHO, 2000). The relationship between obesity and hypertension appears to be non-linear and exists throughout the non-obese range. Obesity by itself possibly accounts for 78% and 65% of essential hypertension in men and women, respectively, according to data from the Framingham Cohort (Kannel et al., 1993). Hyperinsulinemia, hyperleptinemia, hypercortisolemia, renal dysfunction, altered vascular structure and function, enhanced sympathetic and renin/angiotensin system activity, and blunted natriuretic peptide activity stand out as major contributory mechanisms to "obesity - hypertension" (Tuck et al., 1981; Hall et al., 2002; Mansuo et al., 2000; Engeli & Sharma, 2002). Furthermore, according to the European Society of Hypertension and the European Society of Cardiology (ESH-ESC) guidelines, hypertension induces high added risk for target organ damage, diabetes, or associated clinical conditions (ESH-ESC, 2003). Moreover, organ damage and associated clinical condition in obese people increase with the extent of risk factor clustering (Narkiewicz, 2006a). Therefore, objective diagnosis of obesity-hypertension is an important public health challenge because of its high frequency and concomitant risk of cardiovascular and kidney diseases.

Details regarding hypertension risk stratification have been published: 1999 WHO/ISH Guidelines (Chalmers et al., 1999), 2003 ESH-ESC Guidelines (ESH-ESC, 2003), JNC6 of USA (Sheps et al., 1997) and the Guidelines for the Management of hypertension of China (Ministry of Health People's Republic of China, 1999). In what concerns obesity, the evidences from the literature show a continuous relationship between gradation of body mass index (BMI), waist circumference, waist to hip ratio and

Postolache O., Mendes J., Postolache G. and Silva Girão P. (2009).
ARTIFICIAL NEURAL NETWORK APPROACH FOR OBESITY-HYPERTENSION CLASSIFICATION.
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing*, pages 514-520
DOI: 10.5220/0001553705140520

health risk (WHO, 2000; Sowers et al., 2001; Health Canada, 2003; Lau et al., 2007, Ergun, 2008). Nowadays, diagnosis of obesity is made mainly according to body mass index (BMI) and waist circumference. Unfortunately, comparisons by ethnicity and sex have revealed that the universal application of criteria for obesity and central obesity developed in Caucasians leads to an overestimation of risk in African Americans and an underestimation of risk in South Asians (Sumner et al., 2007). Also, obesity identification by generational trends showed those generations prior to the "Baby Boomer", who were not exposed to more recent unhealthy food consumption patterns as younger people, are less likely to be obese, in spite of their age (Garavagli & Synthelabo, 2004). In addition, geography also plays a role (Garavagli & Synthelabo, 2004). Also, new Canadian Guidelines on the management and prevention of obesity in adults and children emphasised the importance to measure depression and other mood disorders beyond BMI, waist circumference and laboratory parameters (as fasting blood glucose level, total cholesterol, LDL cholesterol, HDL cholesterol, triglycerides, ratio of total cholesterol to HDL cholesterol, liver enzyme levels and urine analysis) (Lau et al., 2007). Moreover, reverse epidemiology it was shown in patients characterized by undergoing haemodialysis, with increased survival of obese patients (Narkiewicz, 2006b, Salahudeen et al., 2006). To deal with these issues, much research is needed to develop improved statistical methods that permit coherent management, taking into account the global risk of a patient with obesity-hypertension rather than to focus solely on biometric variables and blood pressure values. Objective diagnosis of obesity-hypertension is important not only to prevent the progression of obesity and hypertension signalling the health risk but also for treatment management of hypertension in obese people (Dentali et al., 2007; Messerli & Schmieder, 1986, Narkiewicz, 2006a, Narkiewicz, 2006b) reduction of the anaesthesia-related mortality (Saravanakumar et al., 2006), and health costs reduction (WHO, 2008; Lewis & Man, 1999).

The aim of this study now reported was to evaluate the performance of an artificial neural network (ANN) for modeling and objective identification of the obesity-hypertension physiopathology joining different informations related to the patient health status. The ANN, a kind of black box model, shows certain advantages over other methods for multivariate modeling. The major advantage used in the present application is that with sufficient data, an ANN can be trained to learn the relationship between the inputs (clinical examination data) and outputs (obesity-hypertension classes) even if the mechanism of the relationship is unknown or unclear, as in the present case where few models are described in literature for hypertension-obesity stratifications criterion (see Aneja et al., 2004, Narkiewicz, 2006a, Narkiewicz, 2006b). The ANN ensures great flexibility associated with computer diagnosis of the hypertension-obesity sindrome (Ning et al., 2006; Bidiwala et al., 2004; Lapuerta et al., 1995; Mangiameli et al., 2004; Orunescu et al., 2004, Poli et al., 1991). Our application of the ANN permits better diagnosis and management of the obesity-hypertension syndrome.

2 METHODS

The problem in diagnosis and management of obesity is that the relationship between different items (e.g. laboratory results and/or symptoms) is not always well established and that there exists a myriad of exceptions for every rule. A learning process expert system could be developed using neural networks for medical decision aid. The schematic drawing of the model is shown in Fig. 1. The figure includes a multilayer perceptron neuronal network classifier (MLP-NN) whose inputs are expressed by values of clinical examination data.

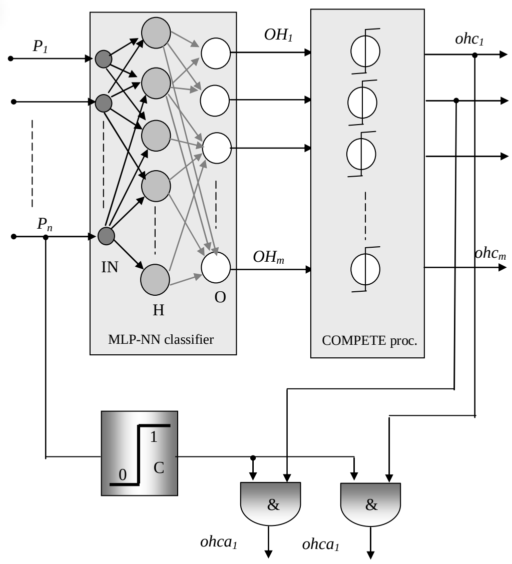

Figure 1: Obesity-Hypertension Neural Network Processing Scheme (ohcm – obesity-hypertension classes, ohca1, ohca2- obesity-hypertension additional classes).

The competitive processing block calculates the binary output (ohc_1, ohc_2 …) using the values obtained with the MLP-NN classifier. Additional classes ($ohca_1$, $ohca_2$) are obtained by using the level of blood-pressure and the hypertension thresholds (e.g. SBP > 140mmHg, DBP > 90mmHg) and the results of competitive processing block for the particular cases of *normal* and *overweight* individuals.

Table 1: Variables range used to describe obesity-hypertension syndrome class 3.

Variables	OHC_3	Normal
Body mass index (kg/m^2)	40-85	18.5-24.9
Waist girth [a] (cm)	150-170	58-88
Waist-to-hip ratio (cm/cm)	1.4-1.6	0.6-0.9
Systolic blood pressure (mmHg)	140-190	90-125
Diastolic blood pressure (mmHg)	90-120	55-84
Heart rate (bpm)	90-140	55-95
Serum triglycerides (mg/dL)	200-350	30-175
Total cholesterol (μmol/L)	200-350	250-680
Serum HDL cholesterol (mg/dL)	35-50	50-60
Serum LDL cholesterol (mg/dL)	30-40	50-130
Glucose (mg/dL)	90-220	70-110

A brief description of the main blocks of the obesity-hypertension general classifier is presented next.

2.1 The Input of the Model

In the present study, a model of the clinical parameters distribution that is essential for diagnosis and monitoring was built using published data. The evidences on relation between hypertension and obesity are mainly documented on adult people (18-50 years), overweight, or with class 3 obesity (BMI>40 kg/m^2). However, there are a lack of studies that may give a thorough view on the main clinical indicators (see Aneja et al., 2004), which may better describe the present state of an individual and possible future evolution of hypertension in relation with obesity.

Since there were no well-characterized real datasets available that fit with all obesity classes described in our study, a simulation study was proceed. The input data considered was essential clinical information for obesity-hypertension association, being expressed by the values of the following parameters: body mass index (BMI), waist girth, blood pressure, heart rate, triglyceride, glucose, high-density lipase (HDL)-cholesterol (Aneja et al., 2004), total cholesterol (Ai et al., 2000, Aguilera et al. 2008), low-density lipase (LDL)-cholesterol (Aguilera et al., 2008, Gupta et al., 2007). The simulated values for different obesity classes were adjusted according to the published data applying uniformly random data distribution for specific data intervals. The maximum values for morbid obese group were built taking into account clinical cases of obesity described in 19th century – Daniel Lambert (Table 1). The samples sizes were simulated for 400 to 1600 individuals, 40 to 200 individuals for each class.

The simulated data were not defined using sex-specific observation points. However, a future study taking into account the data distribution versus sex and age will be considered.

Although the parameter settings are not exhaustive in terms of all physiopathological plausible situations, the outlined conditions are reasonable, mainly designed to differentiate obesity and hypertension features.

2.2 The Output of the Model

The classification of the simulated data were made according to 2000 WHO (WHO, 2000b), 2003 Health Canada (Health Canada, 2003) and 2003 ESH-ESC Guidelines (ESH, 2003). Presently, diagnosis of obesity is made mainly according to BMI index:

$$BMI = mh^{-2} \tag{1}$$

where *m*-personal weight and *h*-personal height.

The average BMI index in normal people is between 18.5 and 24.9 kg/m^2. Obesity is defined as a BMI>30 kg/m^2; morbid obesity is when BMI>35 kg/m^2. There is a continuous relationship between gradation of BMI and health risk and between waist circumference and health risk. Hypertension is considered when systolic blood pressure (SBP) is >140 mmHg and diastolic blood pressure (DBP) is >90 mmHg. Current guidelines suggest that essential laboratory investigation for hypertension diagnosis should include: blood chemistry for fasting glucose, total cholesterol, HDL-cholesterol, LDL-cholesterol, triglycerides, urate, creatinine, sodium, potassium, haemoglobin and haematocrit, decreased creatine clearance, liver enzyme, the detection of an elevated urinary excretion of albumin, an electrocardiogram or echocardiography (Narkiewicz, 2006a, Lau et al., 2007). For the sake of application in practice, the input and output of the model was simplified. The output of the model was defined as: healthy subject (N), hypertensive with BMI normal (H), overweight (OW), overweight with hypertension (OWH), obesity class I (OC_1), obesity class I-hypertension (OHC_1), obesity class II (OC_2), obesity class II-hypertension (OHC_2), obesity class III (OC_3), and obesity class III-hypertension (OHC_3).

2.3 Model Architecture and Training

The type of the neural network used in this work was multilayer perceptron (MLP-NN). The network training is based on supervised learning techniques that were implemented and tested for a better classification of the assessed persons. Thus, training algorithms such as Levenberg Marquardt back propagation (LMBP) and Generalized Delta Rule were used.

The MLP-NN classifier architecture includes a set of three layers. The input layer receives a set of normalized values associated with obesity-hypertension clinical examination data that are delivered by the pre-processing block. The number of input nodes was included in the 10 to 19 interval. The hidden layer learns to encode these quantities and includes sigmoidal neurons (logsigmoid, tansignoid). During the MLP-NN design a practical approach concerning the number of hidden neurons for a short training time (t_{train}) and good classification of the individual in the obesity-hypertension classes *OHclass* was performed.

The output layer produces the desired classification results and is expressed by a number of linear neurons n_{out} (8 to 10 neurons). The values associated with the output neurons are included in the [0, 1]. Thus a value near one underlined that an OHclass was identified, while ‘0’ corresponds to no OHclass identification. The description equation of neuronal network classifier is:

$$Y = f_{out}\left(W_{out}\, f_{hidden}\left(W_{hidden} X + B_{hidden}\right) + B_{out}\right) \quad (2)$$

where X is the input and Y is the output, W_{hidden} and W_{out} are the weights of the hidden and output layer neurons, B_{hidden} and B_{out} are their biases, f_{hidden} is a sigmoid function for the hidden layer neurons (logsigmoid and/or tansigmoid in the present application) and f_{out} is a linear function for the output layer neurons.

Referring to the MLP-$NN_{classifier}$ design, different training algorithms were applied for shorter training times and accurate classification. Thus, fast backpropagation algorithms expressed by gradient descent algorithm with momentum and variable learning rate, or Levenberg-Marquardt back propagation algorithm were employed to update the weights and biases of the net in the training process.

The training process requires a set of samples expressed, in the present case, by physiopathological variables associated with the individuals under obesity-hypertension and corresponding known OHclass. During training, the weights and biases in the model are adaptively refined to ensure a relative optimization of the network performance related to the classification capability. As performance measurement functions the sum-square error (SSE) and mean-squared-error (MSE) were used:

$$SSE = \sum_{i=1}^{N} \left(oh_i - nnoh_i\right)^2 \quad MSE = \frac{SSE}{N} \quad (3)$$

where N is the number of input samples, oh_i is the target output imposed for known individual data and $nnoh_i$ is the network output for given weights and biases. The $nnoh_i$ values in the [0, 1] interval. In order to conclude about the obtained OHclass for a given individual, a competitive processing block (based on *compet()* MATLAB function) transforms the real values obtained at the MLP-NN outputs in Boolean values corresponding to one of the OHclasses.

After weights and biases calculation using the above mentioned algorithms, a testing set was employed to validate the neural network classification capabilities using simulated and real values.

3 RESULTS

The model of obesity-hypertension classes has been tested using simulated data and experimental data from a group of 30 voluntary persons. The main characteristics of the persons included in the study are presented in Table 2. The studied group includes 3 subjects with normal BMI, 15 persons with normal BMI and hypertension, 3 overweight persons, 4 overweight with hypertension, 1 person with obesity class I, 1 person with obesity class II, 2 hypertensive subjects with obesity class II and 1 hypertensive subject with obesity class III.

A set of data corresponding to different obesity-hypertension classes, normally and overweight individuals, and the corresponding physio-pathological parameters were used to train the neural processing scheme associated to obesity – hypertension model.

Table 2: The main characteristics of the patients included in the study.

	Median	Average
Age (y)	58.50 (33-87)	60.37
BMI (kg/m^2)	24.37 (18.57-46.88)	25.21
Waist girth (cm)	101.00 (67-131)	100.90
SBP (mmHg)	158.10 (112-189)	161.00
DBP (mmHg)	81.50 (56-101)	78.90
Heart rate (bpm)	75 (60-99)	76.67
Triglyceride (mg/dL)	171 (60-300)	163.37
Total cholesterol (μmol/L)	178 (83-264)	174.27
HDL cholesterol (mg/dL)	44 (21-100)	46.07
Glucose (mg/dL)	84 (68-325)	106.43

The MLP-NN training set was expressed by a 10×400 input matrix and a 10×400 target matrix while the testing set was expressed by a matrix with the same dimensions as the training matrix. Both, training and testing data sets were obtained by simulation according with the values obtained in clinical trials. Additionally, a reduced testing set for clinical trial data expressed by 10×30 input matrix and 8×30 output matrix was used to test the designed processing architecture.

Different neural network architectures were designed and tested. Considering the problem complexity and the amount of data used for training and testing, the MLP-NN with hidden layer characterized by 5 to 15 neurons was employed. Good results were obtained for n_{hidden}=10 logsigmoid neurons. The associated error curve, during the training with SSE=0.2 training stop condition, is shown in Fig. 2.

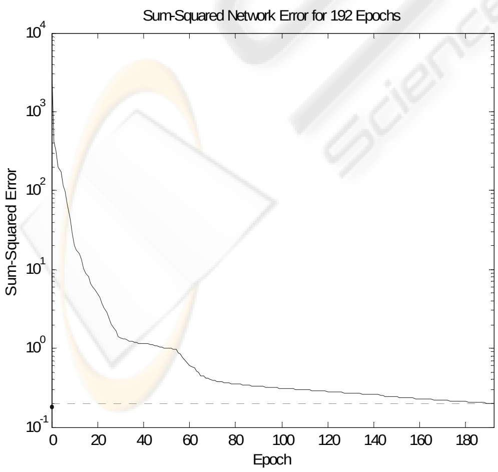

Figure 2: The error curve of the MLP-NN during the training phase (10 logsignoid neurons and SSE=0.2 training stop condition).

The weights and biases values obtained during the training are used to perform the normal (N), overweight (OW) and obesity-hypertension (OH) classification of the individuals using the simulated testing data available for all of eight hypertension and obesity classes. Real testing data was available only for reduced number of classes (N, OW, OC_1, OHC_2 and OHC_3). Several results concerning the classification scheme performance are presented in Table 3 that shows good classification accuracy for ANN training and testing data sets obtained by simulation. Thus, considering testing data obtained by simulation, the output of the neural network classification scheme is expressed by the classification histogram (Fig. 3).

Table 3: Classification results for MLP-NN classifier characterized by 10 logsigmoid hidden neurons.

Class	Total Classification Accuracy	
	Training	Testing
N	97.5%	95%
OW	100 %	97.5%
OC_1	100%	95%
OHC_1	97.5%	72.5%
OC_2	97.5%	97.5%
OHC_2	100%	82.5%
OC_3	97.5%	82.5%
OHC_3	100%	100%

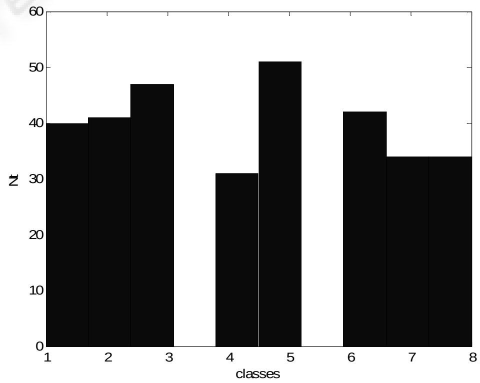

Figure 3: N-OW-OH classification histogram (Nt – number of occurrences).

The accuracy of the ANN classifier for real clinical data associated with the diagnosis of the 30 volunteers was included in the study and the results are represented in Table 4. As can be observed in the table, the used real data include several of the considered classes caused by limited number of the data provided by the Hypertension Hospital Service.

Table 4: Accuracy of the ANN model for classification of individuals from experimental group (30 individuals).

Class	N	OW	OC_2	OHC_2	OHC_3
Accuracy	27%	57.14%	100%	50%	0%

Considering that the experimental group includes individuals associated with N and OW classes and less in the obesity classes (OC1, OHC2, OHC3) the very low or very high classification success in several classes is expected. Better results are expected to be obtained when an extended experimental data for each OH classes will be used for the designed ANN classifier.

4 CONCLUSIONS

There is a lot of knowledge on obesity, but thoroughly view of the phenomenon remains to be done. The model based on ANN with extended clinical examination data represents an important method for classification of individuals with obesity-hypertension syndrome. A hybrid processing based on backpropagation neural network and competitive processing blocks was developed. Results for simulated and experimental data recommend the implemented processing scheme as a good classifier and decision support tool.

Future work will be dedicated to the increase of the classification accuracy by optimizing the neural network architecture. Additionally, according to the cooperation of the Hypertension Hospital unit, real data for different subjects at different times will be used to extract important information on cardiovascular risk level associated with each obesity-hypertension classe.

ACKNOWLEDGEMENTS

The authors wish to thank Dr[a]. Monica Ferreira (Hospital Santa Maria of Lisbon) for the support to the research activity. The research was funded by the Portuguese Research Foundation - FCT through PTDC/EEA-ACR/75454/2006 research project.

REFERENCES

World Health Organization. WHO. 2000. http://search.who.int/search?q=2025%2C+obesity&btnG=Search&entqr=0&output=xml_no_dtd&sort=date%3AD%3AL%3Ad1&Search=Search&ie=utf8&client=WHO&ud=1&site=default_collection&oe=UTF-8&proxystylesheet=WHO

Kannel, W.B., Garrison, R.J., Dannenberg, A.L. 1993. Secular blood pressure trends in normotensive persons. *Am Heart J*, 125:1154-1158.

Tuck, M.L., Sowers, J., Dornfield, L., Kledzik, G., Maxwell, M. 1981. The effect of weight reduction on blood pressure plasma rennin activity and plasma aldosterone level I obese patients. *N Eng J Med.* 304:930-933.

Hall J.E., Crook, E.D., Jones, D.W., Wofford, M.R., Dubbert, P.M. 2002. Mechanisms of obesity-associated cardiovascular and renal disease. *Am J Med Sci.* 324:127-137.

Mansuo, K., Mikami, H., Ogihara, T., Tuck, M.L. 2000. Weight gain-induced blood pressure elevation. *Hypertension*. 35:1135-1140.

Engeli, S. Sharma, A.M. 2002. Emerging concepts in the pathophysiology and treatment of obesity-associated hypertension. *Curr Opin Cardiol.* 17:355-359.

European Society of Hypertension. Guidelines Committee. 2003. European Society of Hypertension - European Society of Cardiology guidelines for the management of arterial hypertension", *J Hypertens*. 21:1011-1053, http://www.eshonline.org/documents/2003_guidelines.pdf

Narkiewicz, K. 2006a. Diagnosis and management of hypertensionin obesity. *Obesity Reviews*. 7(2):155-162.

Chalmers, J., MacMahon, S., Mancia, G. et al, 1999. 1999 World Health Organization-International Society of Hypertension Guidelines for the management of hypertension. *J Hypertension.* 17:151-183.

Sheps, S.G., Black, H.R., Cohen, J.D. et al, 1997. *The sixth report of the joint national committee on prevention, detection, evaluation and treatment of high blood pressure: the JNC 6 report*. NIH Publication.

Ministry of Health People's Republic of China, China Hypertension League, Drafting Committee for The Guideline. 1999. *Guidelines for the management of hypertension of China (in Chinese)*.

Sowers, J.R., Epstein, M., Frohlich, ED. 2001. Diabetes, hypertension, and cardiovascular disease: an update. *Hypertension.* 37(4):1053-1059.

Health Canada. 2003. *Canadian guidelines for body weight classification in adults,* http:/ / www.hc-sc.gc.ca/ fn-an/ alt_formats/ hpfb-dgpsa/ pdf/ nutrition/ weight_book-livres_des_poids_e.pdf.

Lau, D.C.W., Douketis, J.D., Morrison, K.T., Hramiak, I.M., Sharma, A.M., Ur, E. 2007. 2006 Canadian clinical practice guidelines on the management and prevention of obesity in adults and children. *CMAJ.* 176(8):S1-S10.

Ergun U. 2008. The classification of obesity disease in logistic regression and neural network methods. *Current Cardiovascular Risk Reports*. 1(2): 97-101.

Sumner, A.E., Ricks, M., Sen, S., Frempong, B.A. 2007. How current Guidelines for obesity underestimate risk in certain ethnicities and overestimate risk in others. *Current Cardiovascular Risk Reports*. 1(2):97-101.

Garavaglia, S.B., Synthelabo, S. 2004. Generational trends in obesity in the United States: analysis with a wavelet coefficient self-organizing map. *Proceedings. 2004 IEEE International Joint Conference on Neural Networks*. 1:769-774.

Narkiewicz, K. 2006b. Obesity and hypertension-the issue is more complex than we thought. *Nephrol Dial Transplant*. 21(2):264-267.

Salahudeen, A.K. 2006. The obesity paradox as it relates to survival and hypertension in dialysis patients. *Nephrol Dial Transplant*. 21(6):1729-1729.

Dentali, F., Sharma, A.M., Douketis, J.D. 2005. Management of hypertension in overweight and obese patients: A practical guide for clinicians. *Curr Hypertens Rep*. 7(5):330-336.

Messerli, F.H., Schmieder, R.E. 1986. Use of diuretic agents in obese or black patients with systemic hypertension. *Am J Cardiol*. 58(2):11A-14A.

Saravanakumar, K., Sudarsan, G.R., Cooper, G.M. 2006. The challenges of obesity and obstetrics anaesthesia. *Curr Opin Obstet Ginec*. 8(6):631-635.

World Health Organization, WHO, 2008. http://www.who.int/dietphysicalactivity/publications/facts/obesity/en/

Lewis, K.K., Man, L.H. 2007. Overweight and obesity in Massachusetts: epidemic, hype or policy opportunity? *Policy Brief, The Massachussetts Health Policy Forum*. http.//masshealthpolicyforum.bradeis.edu.

Aneja, A., El-Atat, F., McFarlane, S.I., Sowers, J.R. 2004. Hypertension and obesity. *Rec Progr in Hormone Res*. 59:169-205.

Ning, G. Su, J., Li, Y., Wang, X., Li, C., Yan, W.,Zheng X. 2006. Artificial neural network based model for cardiovascular risk stratification in hypertension. *Med Biol Eng Comput*. 44:202-208.

Bidiwala, S., Pittman, T. 2004. Neural network classification of pediatric posterior fossa tumors using clinical and imaging data. *Pediatr Neurosurg*. 40(1):8-15.

Lapuerta, P., Azen, S.P., LaBree, l. 1995. Use of neuronal network in predicting the risk of coronary artery disease. *Comp Biomed Res.* 28:38-52.

Mangiameli, p., West, D., Rampal, R. 2004. Model selection for medical diagnosis decision support systems. *Decision support Syst*. 36(3):247-259.

Orunescu, E., Bagnasco, M., Salmaso, C. Altrinetti, V., Bernasconi, D, DelMonte, P., Pesce, G., arugo, m., Mela, G.S. 2004. Use of an artificial neural network to predict Graves' disease outcome within 2 years of drug withdrawal. *Eur J Clin Invest* 34(3):210-217.

Poli, R., Cagnoni, S., Livi, R., Coppi, G., Vali, G. 1991. A neural network expert system for diagnosing and treatinghypertension. *Computer* 24(3):64-71.

Mangiameli, P. West, D., Rampal, R. 2004. Model selection for medical diagnosis decision support systems. *Decision Support Syst*. 36(3):247-259.

Ai, M., Tanaka, A., Ogita, K., Sekine, M., Numano, F., Numano, F., Reaven, G.M. 2000. Relationship between hyperinsulinemia and remnant lipoprotein concentrations in patients with impaired glucose tolerance. *J Clin Endocrinol Metab*. 85(10):3557-3560.

Aguilera, C.M., Gil-Campos, M., Cañete, R., Gil, A. 2008. Alterations in plasma and tissue lipids associated with obesity and metabolic syndrome. *Clin Sci (Lond*). 114(3):183-193.

Gupta, R., Rastogi, P., Sarna, M., Gupta, V.P., Sharma, S.K., Kothari, K. 2007. Body-mass index, waist-size, waist-hip ratio and cardiovascular risk factors in urban subjects. *J Assoc Physicians India.* 55: 621-627.

World Health Organization. WHO. 2000b. Obesity: Preventing and Managing the Global Epidemic. WHO Obesity Technical Report Series No. 894 World Health Organization, Geneva, Switzerland.