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Procedia Computer Science 57 (2015) 1115 – 1123

Procedia Computer Science

3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015)

Evaluation of low bone mineral mass using a combination of peripheral bone mineral density and total body composition variables by neural network

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Abstract

The aim of this work was to evaluate low bone mass using the feed-forward neural network (NN) with good accuracy taking into account the forearm and heel bone mineral density (BMD) as well as total body composition variables. A total number of 162 subjects including 88 women (mean ± SD age = 37.7 ± 15.2 years) and 74 men (mean ± SD age=31.3 ± 10.9 years) were studied. In each subject, BMD (g cm-^{2}) at forearm and heel using peripheral dual-energy X-ray absorptiometry (pDXA) and total body composition variables by multifrequency bioelectrical impedance analyzer were measured. The measured forearm BMD was used to estimate femur neck BMD by DXA using the published formula. Based on its T-score value, subjects were classified as normal and low bone mineral mass groups separately. In women, it was found that the forearm BMD was positively correlated with body fat percentage (r=0.327; p<0.001). It was observed that 27% of women and 15% of men were affected by low bone mass. In the NN modelling, the following 10 measured variables were used in men and women separately: i) BMI ((kg/m^2); ii) average forearm BMD (g/cm^2); iii) average heel BMD (g/cm^2); iv) body fat (%); v) muscle mass (kg); vi) visceral fat index; vii) bone mineral mass (kg); viii) total body water, TBW (%); ix) basal metabolic rate, BMR (kCal); and x) metabolic age (years). Analysis of low bone mineral mass evaluation using NN projected an accuracy of 87.5% and 85.1% in women and men population, respectively. With the aid of BMD at peripheral skeletal sites and total body composition variables, low bone mass can be evaluated with good accuracy.

Peer-review under responsibility of organizing committee of the 3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015)

Keywords- Bone mineral density, pDXA, Total body composition, Osteoporosis, Low bone mineral mass, Neural network

1. Introduction

‘Osteoporosis’ is a widespread clinical problem in India and throughout the world. It is a systemic skeletal disease characterized by low bone mineral density (BMD) and micro-architectural deterioration of bone tissue with a consequent increase in bone fragility.[1] In osteoporosis, the bones become fragile and easily brittle. The most commonly affected skeletal sites are hip, spine, and wrist. It is an asymptomatic disease, reflected only at

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Peer-review under responsibility of organizing committee of the 3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015)
doi:10.1016/j.procs.2015.07.398

low BMD condition, and is known only when a fracture occurs. Similar to a high probability of predisposition to stroke in asymptomatic hypertension, low BMD predisposes the affected population to osteoporotic fracture. With increasing general longevity of the Indian population, it is now being realized that, as in the West, osteoporotic fractures are a major cause of morbidity and mortality in the elderly.[2] On the basis of 2001 census, approximately 163 million Indians are above the age of 50 years; this number is expected to increase to 230 million by 2015.[2] Even conservative estimates suggest that of these, 20% of women and about 10-15% of men would be osteoporotic. The total affected population would, therefore, be around 25 million. If the lower bone density is shown to confer a greater risk of fracture, as is expected, the figure can increase to 50 million.[3] The first quantitative method to detect low BMD was single-photon absorptiometry (SPA); it was used to measure BMD in the peripheral skeleton, particularly the radius, and it used a gamma-emitting radioactive source.[5] SPA was extended to dual-photon absorptiometry (DPA), which allowed measurements to be made at more important sites of osteoporotic fracture in the central skeleton such as spine and hip. SPA and DPA have been superseded by single-energy X-ray absorptiometry (SXA) and dual-energy x-ray absorptiometry (DXA), respectively; in both these methods, the radionuclide has been replaced by an x-ray tube as the radiation source. In particular, DXA has become established as the reference 'gold standard' technique for measuring BMD at both peripheral and central skeletal sites. Its main advantages are low radiation dose and high precision (reproducibility). A peripheral dual-energy x-ray absorptiometry (pDXA) bone densitometer is a special portable device that is used to measure BMD at peripheral skeletal sites such as forearm, finger and heel. Like central DXA, pDXA measurements can predict the risk of future osteoporotic fracture. Compared with central DXA, the advantages of pDXA include portability, low capital and operational costs, minimal operational space, and even lower patient radiation dose.[6] Body composition refers to the physical material that makes up the body. Because of the health effects of excess body fat (e.g., increased risk of type 2 diabetes, heart disease, cancer) and of being underweight (e.g., anorexia nervosa), quantifying body composition in terms of percent fat has important uses. Methods of body composition assessment include underwater weighing, skin fold thickness, air-displacement plethysmography, bioelectric impedance analysis. Bioelectric impedance analysis is an easily administered technique to determine a variety of parameters and it is cheap and safe. Artificial neural networks (ANN) are now widely used in predicting and diagnostic systems. Pattern recognition is accomplished by fine tuning the parameters of the ANN by minimizing errors through the process of learning from experience. They can be attuned by any number of input data and output can be sorted to any number of given categories. The purpose of this study was to evaluate an individual for low bone mineral mass with good accuracy using a combination of BMD and total body composition variables by an artificial neural network (ANN).

2. Materials and methods

2.1. Subjects

A total number of 173 Indian men and women of aged 20 years and more participated in this pilot study, which was conducted at the campus of SRM University, Kattankulathur, Tamil Nadu, India, during the months from September to October 2014. The participants with chronic liver or kidney diseases, malignancy, malabsorption syndrome, inflammatory arthritis, hypo- or hyper- thyroidism, previous gastrointestinal surgery or osteoporotic fractures were excluded. Also excluded were those on chronic medications known to affect bone metabolism (e.g., thiazides, diuretics, estrogen). After applying the aforementioned exclusion criteria, the remaining 162 participants including 88 women (mean ± SD age = 37.7 ± 15.2 years) and 74 men (mean ± SD age=31.3 ± 10.9 years) were included in the study analysis. An informed consent was obtained from all the participants. Basic health history of each participant was obtained with the help of a simple questionnaire, prepared for the study.

2.2. Measurements

In each participant, the BMD (g cm^{-2}) of bilateral sides of both forearm and heel was measured at standard conditions using a peripheral DXA bone densitometer (EXA-3000, Osteosys Corporation, Seoul, Korea). By combining the measured bilateral side measurements, an average BMD of both forearm and heel was calculated for each participant. A quality assurance test for the device was performed on each day of this measurement using a manufacturer-provided BMD phantom to ensure its accuracy. Also in each participant, total body composition analysis was carried out under standard condition using a body composition analyzer (MC 780MA, Tanita, Japan). The measured parameters are as follows: i) body fat (%); ii) muscle mass (kg); iii) visceral fat index; iv) bone mineral mass (kg); v) total body water, TBW (%); vi) basal metabolic rate, BMR (kCal); and vii) metabolic age (years).

2.3. Evaluation of low bone mineral mass

In each participant, the equivalent femur neck BMD value was predicted from the measured average forearm BMD value, using a formula suggested by Marwaha et al [femur neck BMD, g cm^{-2} = (0.706 × forearm BMD, g cm^{-2}) – 0.440]. The World Health Organization (WHO) has established criteria for making the diagnosis of osteoporosis, as well as determining levels that predict future osteoporotic fractures. The criterion is based on comparing the measured BMD (of either femur or spine by DXA) of an individual with that of a typical healthy, sex-matched young normal group. A standardized score, called 'T-score', is used to define the categories. T-score is calculated as: T-score = [(measured BMD value – sex-matched young adult mean BMD value)/sex-matched young adult SD value]. Based on the calculated T-score value, the total men and women studied were classified into two groups as follows: a). normal (T-score −1.0 and above); b) low bone mineral mass (T-score below −1.0).

a). Men: Group-I: Normal= 63, mean ± SD age= 31.1±10.0 years
Group-II: Low bone mineral mass=11, mean ± SD age= 31.9±15.5 years

b). Women: Group-I: Normal= 64, mean ± SD age= 33.6±12.9 years
Group-II: Low bone mineral mass=24, mean ± SD age= 48.7±15.6 years

2.4. Analysis

The data were analysed using IBM SPSS/PC statistical software, version 21 (IBM Corp., Armonk, NY, USA). Using SPSS software, Student's t-test was used to compare baseline characteristics between normal and low bone mass groups in men and women population individually. Pearson's correlation coefficients were calculated to analyze the relationship between BMD and other influencing variables. Scatter plots were used to investigate the possible relationship between two variables. A straight line of best fit (using the least squares method) was included.

2.5. Artificial neural network (ANN)

The ANN toolbox in MATLAB 2014 was used. In the modelling, the following 10 measured variables were used in men and women separately: i) BMI ((kg/m^2); ii) average forearm BMD (g/cm^2); iii) average heel BMD (g/cm^2); iv) body fat (%); v) muscle mass (kg); vi) visceral fat index; vii) bone mineral mass (kg); viii) total body water, TBW (%); ix) basal metabolic rate, BMR (kCal); x) metabolic age (years). As mentioned in Section 2.3, the total studied men and women were grouped into the following two groups: i) normal and ii) low bone mineral mass group. The total data set is fragmented into two sets of data namely, training and testing set. The former consists of 62 training data in women population and 52 training data in men population and the latter consists of 13 and 11 testing data in women and men population, respectively. The acquired data were converted into 7 × 88 (for women) and 11 × 74 (for men) matrix forms and were fed into the system. Similarly, for the testing data, 7 × 13 and 7 × 11 data were used for women and men, respectively. Back propagation algorithm was used and the target was set as either '0' for normal group or '1' for low bone mineral mass group. In this work, the ANN proposed as multilayer feed-forward model consists of 7 and 11 input neurons for women and men, respectively, and one hidden layer with 3 hidden neurons carefully chosen so as not to increase the number of neurons leading to overspecialization of the network and in turn routing to loss of generalizing capacity. One output neuron was used to determine the presence of low bone mineral mass of an individual under consideration. The receiver operating characteristic (ROC) analysis was performed, and it was used to depict the performance of the system in evaluating an individual for low bone mineral mass.

3. Results

The baseline characteristics (mean±SD) of all the participants grouped into normal and low bone mineral mass categories in men and women population are listed in Tables 1 and 2, respectively. As expected, the measured mean values of BMI, forearm BMD, bone mineral mass, visceral fat, muscle mass, and BMR were higher among men in the normal bone mineral mass group than among women in the normal group and were found to be statistically significant at $p<0.01$.

Table 1. Baseline characteristics for men

Total Men (N=74)			
Variables	**Normal N=63**	**Low bone mass N=11**	**Statistical significance**
Age (years)	31.1±10.0	31.9 ± 15.5	NS*
BMI (kg/m^2)	23.8 ±3.9	22.7 ± 4.2	0.041
p-DXA- BMD measurements			
Average forearm BMD (g/cm^2)	0.518 ± 0.06	0.469 ± 0.063	0.015
Average heel BMD (g/cm^2)	0.577 ± 0.096	0.515 ± 0.114	NS
Total body composition			
Body fat (%)	22.1 ± 5.0	21.9 ± 6.1	NS
Visceral fat index	9.0 ± 5.7	7.6 ±4.5	NS
Muscle mass (kg)	51.307±6.314	44.172±8.645	0.002
Bone mineral mass (kg)	3.113 ± 2.413	2.536 ± 0.291	NS
TBW (%)	50.2 ± 6.6	50.6 ± 4.5	NS
BMR (kCal)	1540.34 ± 205.94	1376.82 ± 189.67	0.017
Metabolic age (years)	33.6 ± 12.2	34.1 ± 13.5	NS

*NS, not significant

Table .2 Baseline characteristics for women

Total Women (N=88)			
Variables	**Normal** N=64	**Low bone mass** N=24	**Statistical significance**
Age (years)	33.6 ± 12.9	48.7 ± 15.6	0.000
BMI (kg/m^2)	26.3 ± 4.9	22.4 ± 3.9	0.001
p-DXA- BMD measurements			
Average forearm BMD (g/cm^2)	0.454 ± 0.040	0.326 ± 0.052	0.000
Average foot BMD (g/cm^2)	0.470 ± 0.077	0.357 ± 0.107	0.000
Total body composition			
Body fat (%)	38.158 ± 7.260	32.920 ± 7.208	0.003
Visceral fat index	7.0 ± 3.9	6.3 ± 3.3	NS
Muscle mass (kg)	36.320 ± 2.843	32.863 ± 5.000	0.000
Bone mineral mass (kg)	2.205 ± 0.273	1.938 ± 0.355	0.000
TBW (%)	44.3 ± 5.5	46.2 ± 6.8	NS
BMR (kCal)	1207.31±117.45	1055.79 ± 148.94	0.000
Metabolic age (years)	43.0 ±12.7	46.1 ±13.8	0.000

*NS, not significant

As shown in Table 3, in all women studied (n=88), the average forearm BMD was found to have statistically significant correlation (p=0.01) with the following variables: BMI (r=0.380), body fat% (r=0.327), bone mineral mass (r=0.393), muscle mass (r=0.403), and BMR (r=0.491). On the other hand, in all men studied (n=74), it was found that, the average forearm BMD value did not have statistically significant correlation with any total body composition parameters. Figure 1 shows the statistically significant correlation of forearm BMD with body composition parameters in women population.

Table 3. Statistical correlation coefficient (r) matrix between forearm BMD and variables measured in all women

Total women (N=88)	
BMI and Total body composition variables	**Average Forearm BMD ($g\ cm^{-2}$)**
BMI (kg/m^2)	0.380**
Body fat (%)	0.327**
Bone mass (kg)	0.393**
Muscle mass (kg)	0.403**
BMR (kcal)	0.491**

**Correlation coefficient (r) was statistically significant at the 0.01 level (2-tailed)

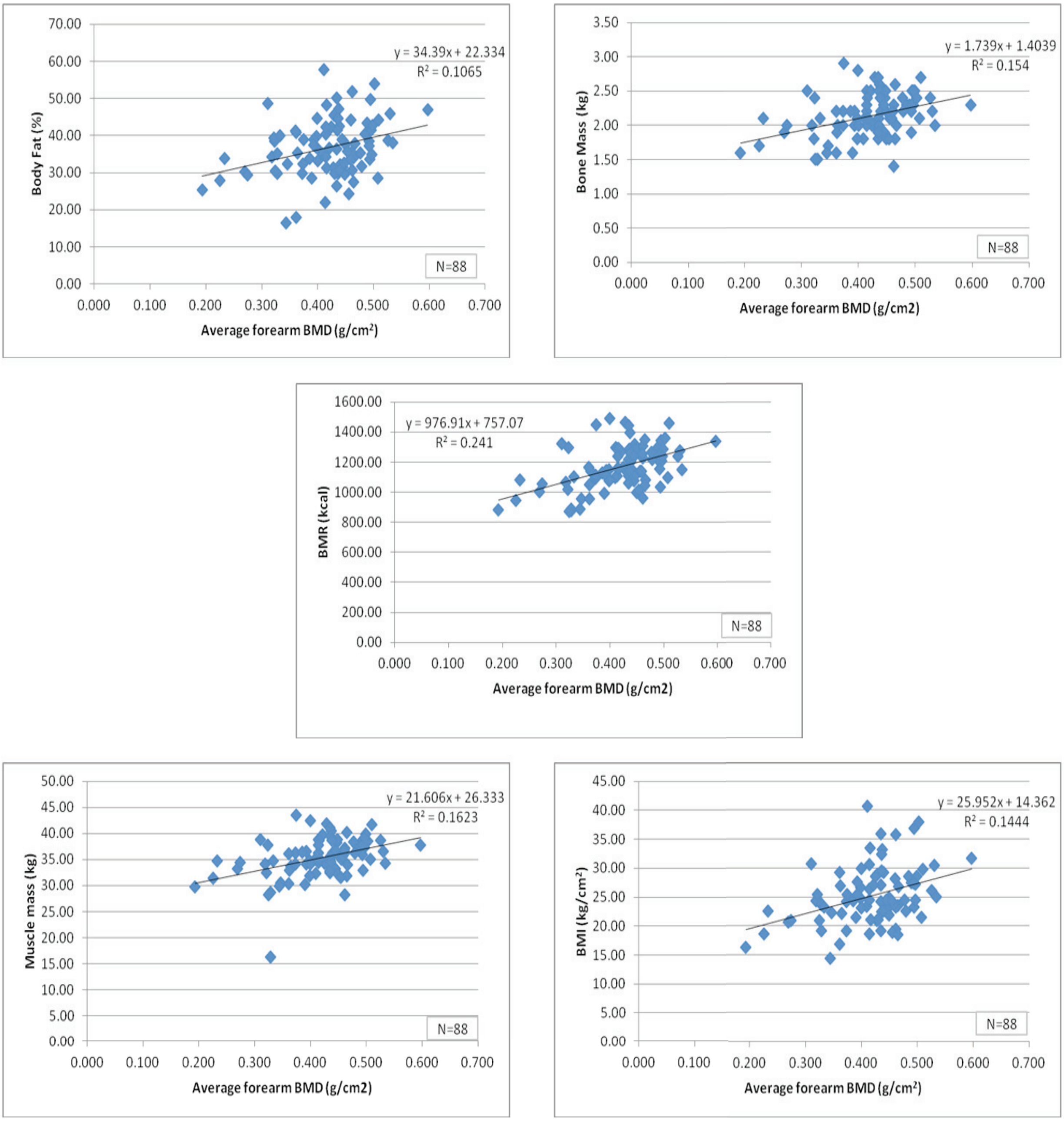

Fig. 1. Statistical correlation between average forearm BMD and various body composition parameters in all women

Tables 4 and 5 display the summary of the results obtained from training using back propagation neural networks to evaluate the presence of low bone mineral mass. In men and women population studied, the accuracy of the modelling was found to be 85.1%, and 87.5% respectively. The ROC curves were also plotted.

Table 4. Performance table for the artificial neural network trained with back propagation

Artificial neural network	**Women**	**Men**
No. of training Samples	62	52
No. of testing samples	13	11
No. of input neurons	7	11
No. of hidden neurons	3	3
No. of output neurons	1	1
Performance	0.502	0.673

Table 5. Results of ANN for both men and women

	Women	**Men**
True Negative	62	61
False Negative	9	9
False Positive	2	2
True Positive	15	2
Accuracy	87.5 %	85.1 %
Sensitivity	62.5 %	18.2 %
Specificity	96.9 %	96.8 %
Positive Predictive Value	88.2 %	50.0 %
Negative Predictive Value	87.3 %	87.1 %

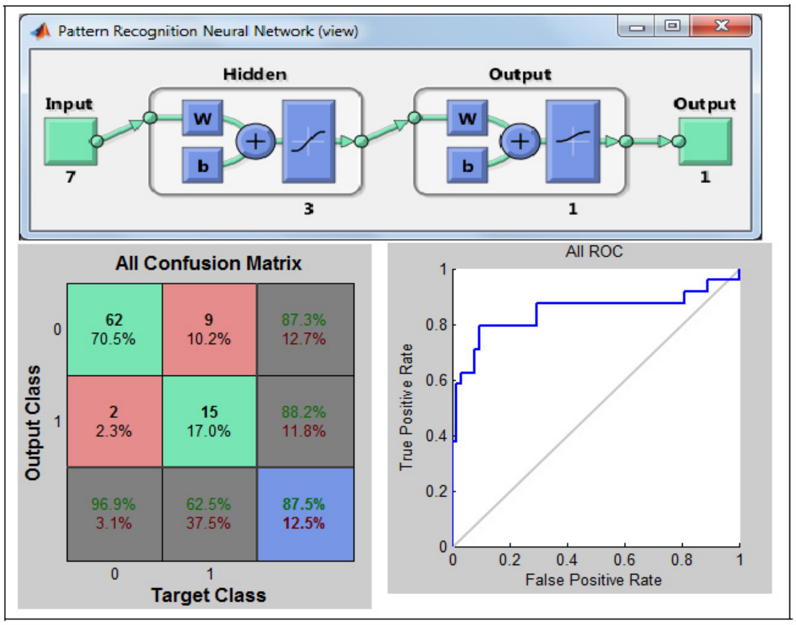

Fig. 2. Results of Neural Networks for women population

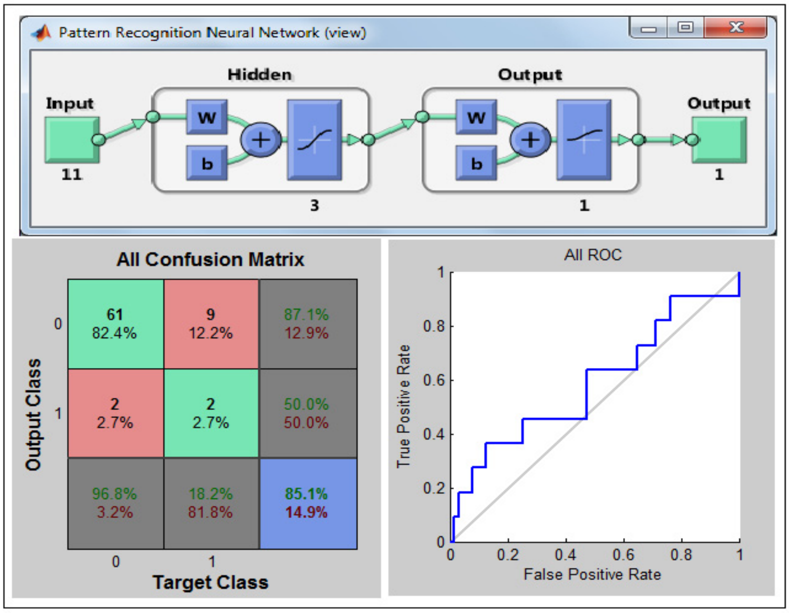

Fig. 3. Results of Neural Networks for men population

4. Discussion

Obesity is usually associated with protection against osteoporosis.[7] Mechanical loading stimulates bone formation by decreasing apoptosis and increasing proliferation and differentiation of osteoblasts and osteocytes.[8] Hence, the assumption of mechanical loading due to body weight has led to the belief that obesity may prevent bone loss and osteoporosis.[9,10] It is well established that BMI is positively correlated with BMD. The present study is in agreement with that correlation. The sex difference of this correlation may be due to production of estrogen by adipose tissue in women. Some studies reported that muscle mass and strength have significant positive associations with BMD.[11–13] A significant correlation was observed in female population in our study as well. The BMD at forearm is found to be significantly associated with the BMD at axial sites.[14] Hence, the classification based on the T-scores was evaluated using neural networks. In this work, back propagation algorithm has been used in neural networks, and the accuracy was found to be satisfactory. Chang et al (2012) selected 5 factors such as BMD, fracture experience, hand grip strength, intake of coffee, and peak expiratory flow rate as inputs to the artificial neural network to predict the hip fracture probabilities. They incorporated genetic algorithms and achieved better area under ROC curve compared to their previous study. Olaniyi et al (2014) constructed a back propagation neural network to classify patients into those with and without diabetes mellitus. They compared their accuracy results with those of other algorithms and found that back propagation network has higher success rates. This work can be extended to check the results with various other algorithms and the best one may be found out.

Acknowledgements

We extend our sincere gratitude to Mrs. Jayanthi Thiruvengadam for her timely help and support.

References

1. World Health Organization (WHO) Technical Report Series 921, "Prevention and Management of Osteoporosis", Geneva: WHO, 2003.
2. Nordin BEC. International patterns of osteoporosis. *Clin Orthop* 1966; 45: 17-30.
3. Gupta AK, Samuel KC, Kurian PM, Rallan RC. Preliminary study of the incidence and aetiology of femoral neck fracture in Indians. *Indian J Med Res* 1967; 55: 1341-8.
4. M. Jergas and H. K. Genant , Quantitative bone mineral analysis In: *Diagnosis of Bone and Joint Disorders*, vol. 4 , pp. 1854-1884 D. L. Resnick, Ed. Philadelphia: W B Saunders Company 1995.
5. J. R. Cameron and J. A. Sorenson . Measurement of bone mineral invivo: an improved method, *Science* 1963, vol. 142, pp. 230-232.
6. D. B. Hans, J. A. Shepherd, E. N. Schwartz, D. M. Reid, G. M. Blake, J. N. Fordham, T. Fuerst, P. Hadji, A. Itabashi M. A. Krieg and E. M. Lewiecki . Peripheral dual-energy x-ray absorptiometry in the management of osteoporosis: The 2007 ISCD Official Positions, *Journal of Clinical Densitometry 2008*, vol. 11, no. 1, pp. 188-206.
7. Kopelman PG: Obesity as a medical problem. *Nature* 2000, 404(6778):635-643.
8. Ehrlich PJ, Lanyon LE: Mechanical strain and bone cell function: a review. *Osteoporos Int* 2002, 13(9):688-700.
9. Felson DT, Zhang Y, Hannan MT, Anderson JJ: Effects of weight and body mass index on bone mineral density in men and women: the Framingham study. *J Bone Miner Res* 1993, 8(5):567-573.
10. Ravn P, Cizza G, Bjarnason NH, Thompson D, Daley M, Wasnich RD,McClung M, Hosking D, Yates AJ, Christiansen C: Low body mass index is an important risk factor for low bone mass and increased bone loss in early postmenopausal women. Early Postmenopausal Intervention Cohort (EPIC) study group. *J Bone Miner Res* 1999, 14(9):1622-1627.
11. Bevier WC, Wiswel R, Pyka G, Kozak K, Newhal K, Marcus R. Relationship of body compositon, muscle strength and aerobic capacity to bone mineral density in older men and women. *I Bone Miner Res* 1989;4:421-32.
12. Kritz-Silverstein D, Baret-Conor E. Grip strength and bone mineral density in older women. *I Bone Miner Res* l94;9:45-51.
13. Hughes VA, Frontera WR, Dalal GE, Lutz 1G. Fisher EC, Evans WJ. Muscle strength and body compositon: asociations with bone density in older subjects. *Med Sci Sports Exerc* l95;27:967-74.
14. S Ozgocmen, B Karaoglan, O B Cimen, Z R Yorgancioglu Relation between Grip Strength and Hand Bone Mineral Density in Healthy Women Aged 30-70. Singapore Med J Vol 41(6) : 268-270 (2000).