Use of artificial intelligence for identification of increased risk of osteoporosis development in postmenopausal women

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Abstract—**This paper presents an Artificial Nerual Network (ANN) for identification of postmenopausal women who are at high risk for developing osteopathy. While 800 patients took part in the study, 180 were used for network training. The following parameters were used: T-score (from -2,5 to -4), Age, Blood calcium level (<1,9 mmol/L), Blood vitamin D level (<20 ng/ml), Hip fracture, Spine fracture, Joint fracture, Glucocorticoids use, Smoking status, and BMI. The network has 10 input parameters and 1 output parameter. For the final architecture of expert system, a neural network with 20 neurons in hidden layer was chosen based on the training results. The signal from each neuron from hidden layer is directed to neuron in output layer, where this neuron processes the signal and gives desired output of the network. The sensitivity was 97,5%, specificity 70%, and accuracy 94,44%.**

Keywords-Osteoporosis, risk assessment, postmenopausal women, Artificial Neural Network

I. INTRODUCTION

Osteoporosis is a skeletal illness that causes weakening of the bones, which can lead to increased fractures. People with osteoporosis have decreased bone mass and microarchitectural degeneration of bone tissue, in addition to lower bone strength [1-3].

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According to data from 2010, 6,6% of men and 22,1% of women over 50 in the EU have osteoporosis. Because of the expanding number of patients worldwide, it is now referred to as a "silent epidemic." Variable and non-variable factors that raise the chance of developing osteoporosis and bone fractures can be separated. One of the most important variables is smoking, which is linked to decreased bone resistance to mechanical stresses and friction. The effects of excessive alcohol use on bone homeostasis are significant. Caffeine, glucocorticoid therapy, insufficient calcium and vitamin D intake, insufficient physical activity, low BMI, past bone fractures, and a family history of osteoporosis are all risk factors [4-6].

Menopause, a decline in estrogen levels, sex hormones needed for regular bone growth and development, is the cause of osteoporosis in the 50s. The generation of osteoclasts increases in the absence of estrogen, resulting in greater bone resorption. Local bone architecture is disturbed as a result of cortical and spongy bone loss. Reduced bone mass, reduced strength, and finally bone fractures result from such changes. According to the World Health Organization, osteoporosis affects 30% of all postmenopausal women [7,8]. T-score is the most common way to describe bone mineral density, and a Tscore of less than or equal to -2.5 on the lumbar spine, femoral, neck, and/or hips is the usual criterion for diagnosing osteoporosis in postmenopausal women [4,7]. Densitometry, mainly DXA, is used to make the diagnosis (dual X-ray absorptiometry). Due to its high cost, the method of assessing bone mineral density with DXA is not frequently suggested [7], so it has been proposed that bone mineral density assessments be performed only in people who have osteoporosis risk factors.

Various epidemiological studies have identified risk variables for osteoporosis in order to construct a risk assessment index, with age and weight being one of the most basic. The risk assessment index is used to identify women who are more likely to have poor bone mineral density and can then be referred for testing [8,9].

In medicine, artificial intelligence (AI) is a field of computer science that can evaluate complex medical data and is a technology that can assist clinicians in improving patient outcomes. Machine learning is a domain of artificial intelligence that has applications in practically every medical sector [10-17], including the diagnosis of osteoporosis and bone fracture prediction using clinical and imaging data [18,19].

Machine learning algorithms have previously been developed to acquire a high capacity to predict the risk of osteoporosis in postmenopausal women. The Artificial Neural

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Network model was shown to be the best of all models employed in the study Shim et al. (2020), leading to the conclusion that using it for medical purposes can aid physicians in the early detection and prevention of osteoporosis in postmenopausal women [20].

The aim of this paper is to employ artificial intelligence in conjunction with several risk indicators to identify postmenopausal women who are at high risk for osteoporosis.

II. METHODS

A. Dataset

For the development of expert system, database containing following parameters was used:

1. T-score
2. Age
3. Blood calcium level
4. Blood vitamin D level
5. Hip fracture
6. Spine fracture
7. Joint fracture
8. Glucocorticoids use
9. Smoking status
10. BMI

These parameters are obtained according to several researches regarding this topic [21-23].

The presented dataset contains 180 samples distributed in two categories: (1) heatlhy subjects and (2) subjects with disease. The output is in categorical form either 0 or 1. The dataset consists of 20% samples of 0 (Minority class) and 80% samples of 1 (Majority class).

During development of the expert system, the aspect of imbalance data was taken into account as expert systems based on such dataset can evolve as one-sided classifier. The distribution of the dataset is presented in Table 2.

TABLE I. TRAINING AND TESTING DATASET DISTRIBUTION

	Class 0	**Class 1**	**Total**
Training	180	640	
Testing	20	160	**1000**
Total	200	800	

B. Expert system architecture

The purpose of the developed system is to classify instances of postmenopausal women with high risk of developing osteoporosis. For the development of the expert system a feedforward Artificial Neural Network (ANN) is chosen in this study. Due to the fact that the majority class is significantly prevalent in the dataset, the possibility of overfitting was taken into consideration during the performance evaluation. For this purpose, particle swarm optimization (PSO) algorithm was employed as an after step to ensure performance accuracy. For the purpose of choosing the most suitable architecture, different combinations of training algorithms and numbers of neurons in the hidden layer were tested (Table 2). The main performance indicator during the development of ANN is mean square error (MSE). MSE is an indicator of the overall error that the ANN makes for all classification instances. Lower MSE indicates better performance.

TABLE II. ANN ARCHITECTURE DEVELOPMENT

Training algorithm	Number of neurons in the hidden layer	MSE
trainscg	5	3.0458e-07
	10	4.4368e-07
	15	2.6731e-07
	20	1.9891e-07
	25	3.2619e-07
trainlm	5	4.7824e-09
	10	3.2064e-09
	15	1.7952e-08
	20	**1.9993e-09**
	25	3.2746e-09
trainbr	5	4.4767e-09
	10	1.1706e-08
	15	7.9653e-09
	20	5.6835e-09
	25	5.6192e-09

C. Performance evaluation

As a peformance measure confusion matrix with parameters of specificity, sensitivity and accuracy of the network is presented. Parameters are calculated according to equations (1), (2) (3):

$$sensitivity = \frac{true\ positive}{(true\ positive + false\ negative)} \tag{1}$$

$$specificity = \frac{true\ negative}{(true\ negative + false\ positive)} \tag{2}$$

$$accuracy = \frac{(true\ negative + true\ positive)}{(true\ negative + true\ positive + false\ negative + false\ positive)} \tag{3}$$

III. RESULTS AND DISCUSSION

Due to rapid development of AI technology, it has also started to be used in medical sciences, in order to improve healthcare and reduce the costs. The main uses are diagnosis, helping in decision-making and treatment algorithms. While successful implementation may require an improved understanding of the ethical, societal, and economic background, there have been multiple papers which show an ANN potential for its use in healthcare [24]. For instance, Nuhic et al. [25] used ANN in ovarian cancer diagnosis.

In this study an expert system was developed for the purpose of classification of postmenopausal women with high risk of developing osteoporosis. The architecture of the developed system is presented in the Figure 1.

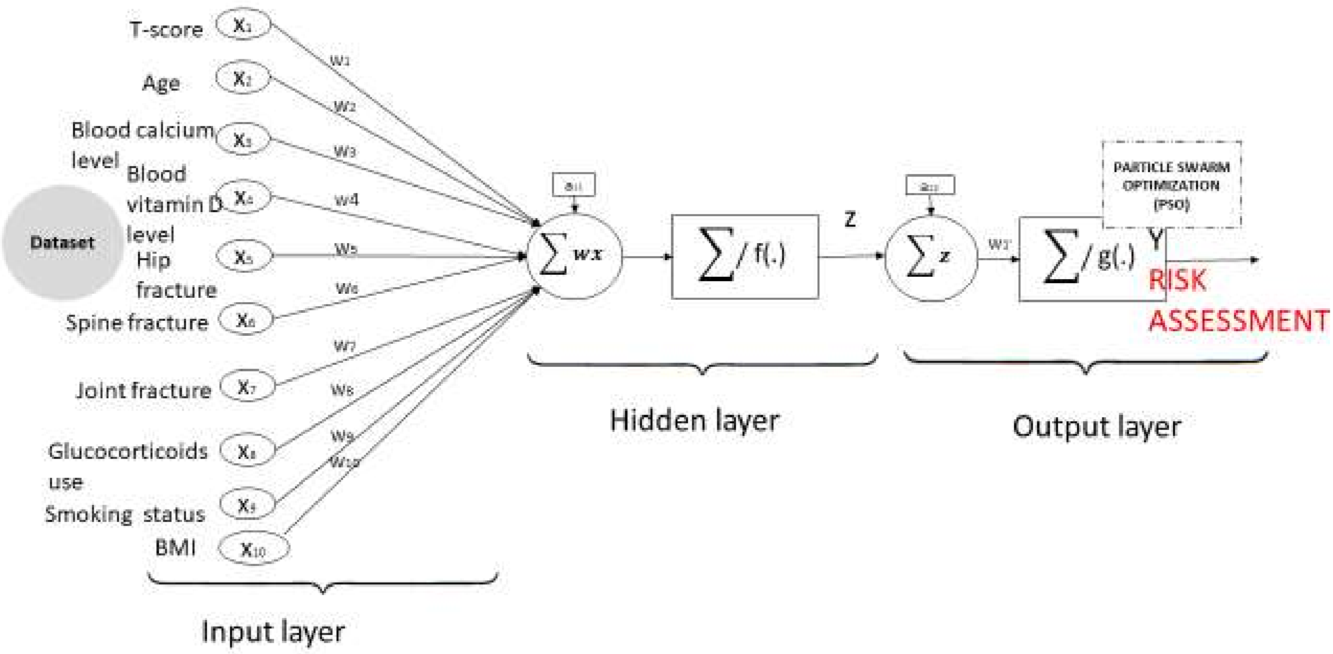

Figure 1. Architecture of the developed system

As mentioned, for classification task in this study feedforward artificial neural network was used. The network has 10 input parameters and 1 output parameter. For the final architecture of expert system, a neural network with 20 neurons in hidden layer was chosen based on the training results. The obtained training performance is 94.18%.

The performance results of ANN testing are presented in Table 3.

TABLE III. SYSTEM PERFORMANCE EVALUATION

	Predicted positive Output class 1	**Predicted negative Output class 0**	**Output class 1 – Subjects with disease Output class 0 – Healthy subjects**
Actual positive 160	True positive (TP) 156	False negative (FN) 4	
Actual negative 20	False positive (FP) 6	True negative (TN) 14	
$\sum$ **180**	Total predicted positive	Total predicted negative	Total units
	Sensitivity 97.5%	Specificity 70.00%	Accuracy 94.44%

IV. CONCLUSION

As osteoporosis in postmenopausal women is a rising problem in the modern world, predictive modelling of the risk of developing osteoprosis is highly desirable. This paper presents the development and validation of an ANN based model for prediction and automated diagnosis of osteoporosis in post-menopausal women based on risk-contributing factors. Giving the high accuracy and sensitivity of proposed ANN for identification of high risk of osteoporosis development in postmenopausal women, it can be concluded that AI has a high potential for decission making for this specific purpose. Prediction of high risk for osteoprosis development can contribute to adjustments in lifestyle and possible prevention of osteoporosis. In addition to the benefit this would have to each individual, the cost reduction in terms of preventing costly interventions necessary in case of osteoporosis development is a significant contribution.

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