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Medical Disease Prediction Using Artificial Neural Networks

Dimitrios H. Mantzaris, George C. Anastassopoulos and Dimitrios K. Lymperopoulos, *Member IEEE*

***Abstract*–This study examines a variety of Artificial Neural Network (ANN) models in terms of their classification efficiency in an orthopedic disease, namely osteoporosis. Osteoporosis risk prediction may be viewed as a pattern classification problem, based on a set of clinical parameters. Multi-Layer Perceptrons (MLPs) and Probabilistic Neural Networks (PNNs) were used in order to face the osteoporosis risk factor prediction. This approach is the first computational intelligence technique based on ANNs for osteoporosis risk study on Greek population.**

MLPs and PNNs are both feed-forward networks; however, their modus operandi is different. Various MPLs architectures were examined after modifying the number of nodes in the hidden layer, the transfer functions and the learning algorithms. Moreover, PNNs were implemented with spread values ranging from 0.1 to 50, and 4 or 2 neurons in output layer, according to coding of osteoporosis desired outcome.

The obtained results lead to the conclusion that the PNNs outperform to MLPs, thus they are proved as appropriate computation intelligence technique for osteoporosis risk factor prediction. Furthermore, the overfitting problem was more frequent to MLPs, contrary to PNNs as their spread value increased.

The aim of proposed PNN is to assist specialists in osteoporosis prediction, avoiding unnecessary further testing with bone densitometry.

I. Introduction

Artificial Neural Networks (ANNs) are subfield of Artificial Intelligence (AI) systems. Their ability to correlate input and corresponding output data [1] – [4], based on vector mapping, has established themselves as a powerful tool in various applications. ANNs have been applied in various medical fields, constituting themselves as a useful technique in clinical practice [5] – [7], such as cardiology [8], oncology [9], pathology, endocrinology [10], radiology [11], urology [12] – [15], pneumonology [16], pediatrics [12], [17] and children surgery [17], [18]. Medicine is a field that ANNs can be proven as a powerful tool to enhance current medical techniques [17] – [21].

This study focus on the development and assessment of ANN pattern recognition models based on both Multi-Layer Perceptrons (MLPs), as well as Probabilistic Neural Networks (PNNs) and the application of these models to the problem of osteoporosis risk factor prediction. More specifically a decision support tool has been developed to help clinicians identify which people are at increased risk for osteoporosis and should therefore undergo further testing with bone densitometry. This application area is considered as extremely important since early detection of osteoporosis is vital for the prevention of osteoporotic fractures, which are associated with increased morbidity and mortality and high socio-economic costs. The proposed ANN architectures and their performance in clinical data are presented in this paper.

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II. Materials and Methods

A. Osteoporosis

Osteoporosis is the prevailing bone's disease, and its features are low bone density mass and the modification of their micro-architecture structure, so that bones' tolerance is reduced and the risk of fracture is increased. Apart from the direct physical implications of a fracture, such as pain and inconvenience, osteoporotic fractures involving the hip or the spine are a major cause of morbidity and mortality. Studies show that two out of five people over seventy-five who fracture a hip will die within a year as a direct result. There is an enormous public health problem with huge recourses required to deal with the immediate and long-term effects of fractures like hospitalization, loss of independence, support at home or in institutions etc. In the European Union one person breaks a bone because of osteoporosis every fifteen seconds.

Often the first apparent symptom of osteoporosis is a broken bone, which is why the condition is also known as "the silent crippler", as people do not realize they have osteoporosis until it's too late. However early detection and treatment of osteoporosis can decrease the fracture risk of a person to a minimum. For these reasons, there are studies [6], [7] where NNs were used for predicting whether a person has osteoporosis or not.

Osteoporosis is presented after the age of 50 years and its frequency increases in proportion with the age. It is most common for women than men. The ordinary type of osteoporosis arises after menopausal. A percentage of 75% of women with osteoporosis, doesn't known their trouble.

The main factor for osteoporosis growth is the high osteal density mass loss between 45 to 50 years of a person. The osteal absorption is greater than osteal production, specific for women elder than 50 years. Thereby, the osteal density

mass loss is prospective.

The osteoporosis diagnosis, both a priori without symptomatic findings or in case of a bone fracture, is based on laboratory examination and the osteal bone densitometry. This examination is applied to specific bones, using Dual Energy X-ray absorptiometry. This technique is based on radiation absorption from the patient, so it is not recommended for entire orthopedic cases.

The osteoporosis data, which were used at the design of ANN models, were obtained from the Orthopedic Clinical Information System of Alexandroupolis' University Hospital, Greece. For each case, there were 4 clinical parameters that have been considered. These parameters were: sex, age, height and weight. The estimation of osteoporosis risk factor was based on T-score value, which is the patient's bone density compared with the normally expected in a healthy young adult of the same sex.

The present study is based on data set consisted of 3426 cases. This data set was divided into a set of 2426 records and another set of 1000 records. The former was used for training of MLP networks and the construction of PNNs, whereas the latter for performance testing of neural networks.

B. Neural Network Models for Osteoporosis Risk Prediction

The proposed pattern recognition models for osteoporosis risk factor classification are based on a non-symbolic computational intelligence method implemented by ANN [12]. The development of such an ANN demands the determination of a number of parameters, such as the type of ANN, the number of neurons in each layer and the applied learning algorithm.

MLPs are feed-forward networks with back-propagation learning rule and are used in majority of ANN models [22], [23]. The correlation of dependent and independent variables constitutes an important feature for MLPs, so they can be used in medical data processing.

A MLP consists of an input layer, where the number of input nodes equals to the number of variables of the problem, and an output layer with a number of nodes defined by the problem's requirements, which presents the simulating results [2]. The hidden layers and a large number of characteristics of MPL architecture would be realized by trial and error.

Although MLPs have been used in a wide range of medical applications, successfully, they are faced with suspicious by many researcher [24], [25]. The reason of this confrontation proceeds by the "black-box" feature of MLPs, as they can detect hidden correlations into data. In contrast to the heuristic feature of MLPs, PNNs, which approximate Bayesian statistical technique, classify patterns with process familiar to human decision makers [26].

PNNs are based on Parzen's Probabilistic Density Function (PDF) estimator [27]. A PNN is a three-layer feed-forward network, consisting of an input layer, a radial basis and a competitive layer. The radial basis layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close every input is to a training input. The third layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a competitive transfer function on the output of the third layer picks the maximum of these probabilities, and produces 1 for that class and 0 for the other classes.

The PNNs do not require iterative learning process, so that may managed magnitude of data faster that MLPs neural networks. This PNNs' feature results by the Bayesian technique's behavior.

The number of neurons for input layer is defined by the problem's parameters. The osteoporosis risk factor prediction is based on four variables; consequently, in this study, the input layer of implemented ANN models consists of 4 neurons. The neurons' number of output layer is defined by both the desired number of problem's variables and the type of ANN. Specifically, the MLP demands a neuron in output layer for estimation of osteoporosis risk factor's stages, as the MLP's result is an integer value of 1 to 4, whereas the PNN architecture uses so many neurons as the number of osteoporosis' stages, that constitute the number of classes of input data.

The development of ANNs demands the data preprocessing. For this study, the sex variable was coded as 1 for female and 2 for male persons, whereas age, height and weight were obtained as recorded in the database. The input parameters of ANNs, as well as their coding are presented in Table I. The 1st column of the Table I corresponds the ANNs' inputs with osteoporosis variables that are presented in the 2nd column. The 3rd column depicts the coding of each variable. The parentheses report the physical correspondence for each variable coding. The values of variables age, height and weight are numerical that correspond to age, height and weight of each patient.

TABLE I.
CODING OF OSTEOPOROSIS CLINICAL PARAMETERS.

NN inputs	Variables	Coding
1	Age	*Numeric value (years)*
2	Sex	*1 (Woman)* *2 (Man)*
3	Height	*Numeric value (cm)*
4	Weight	*Numeric value (kg)*

The output variable of ANNs was the T-score parameter. These values of bone densitometry were classified into 4 stages, as presented in Table II, so their coding is a number according to T-score result.

The used transfer functions of the MLP structure, were two, nominally hyperbolic tangent sigmoid for hidden layer and linear for output layer [28], [29]. The radial basis and competitive transfer functions were applied for hidden and output layer of PNN, correspondingly [28], [29]. Mathematical equations of these transfer functions are

depicted in Table III.

The determination of numbers of neurons for MLP's hidden layer was achieved by trial and error. The Levenberg-Marquardt back-propagation learning algorithm was selected for MLPs' training, as it is a robust algorithm,

TABLE II.
CODING OF T-SCORE VALUES

T-score Value	Coding
≤ - 2.5	1
-2.5 – -1.5	2
-1.5 – 0	3
≥0	4

appropriate for non-linear least-squared problems [28].

The structure of PNNs has only one hidden layer, contrary to MLPs, whereinto the number of hidden layers is not completely defined. Moreover, the number of neurons for PNN's hidden layer depends by the number of patterns during the training phase. Consequently, the proposed PNN had 2426 neurons for hidden layer, as the available data set for PNN implementation, consisted of 2426 cases. PNNs' design is straightforward and does not depend on training, thus no learning algorithm was selected during PNN's implementation [28].

TABLE III.
TRANSFER FUNCTIONS

Transfer Function	Mathematical Equation
Competitive (compet)	Calculates a layer's maximum output from its net input
Hyperbolic tangent sigmoid (tansig)	$f(x) = \frac{2}{1+e^{-2x}} - 1$
Linear (purelin)	$f(x) = x$
Radial basis (radbas)	$f(x) = e^{-x^2}$

The mean squared error (MSE) [28] was used as evaluation criterion of performance of MLPs which mathematical notation is

where N is the number of patterns, t(k), a(k) and e(k) are the

$$MSE = \frac{1}{N}\sum_{k=1}^{N} e(k)^2 = \frac{1}{N}\sum_{k=1}^{N} \left[t(k) - a(k)\right]^2 \qquad (1)$$

desired, the MLP's calculated and the error value for pattern k, respectively.

As mentioned above, the neurons' number of input and output layers is defined by the problem. It was clarified in section 3 that input parameters are 4 and output parameter is one; consequently, in this study, the input layer consists of 4 neurons and the output layer has one neuron that determines the patients' osteoporosis risk factor. The definition of hidden layer is based on the trial and error method. A computational process that modifies the number of neurons in hidden layer and calculates the performance for each of ANN topologies has been implemented.

The PNNs architecture is constrained by the available features of specific problem, however, the width of the calculated Gaussian curve for each probability density function have to be defined. In the present study, this spread factor varied from 0.1 to 50.

III. RESULTS

The development and performance assessment of ANN models were based on MATLAB Neural Network Toolbox, due to its effectiveness and user-friendly interface [28].

The results of implemented MLPs are summarized in Table IV. The 2nd and 3rd columns of this describe architecture of the MLPs and the transfer functions of each ANN's model, correspondingly. The desired MSE for each MLP structure is represented in the 4th column. The percentages of successful prognosis over testing, training and overall data set are presented in 5th, 6th and 7th columns, correspondingly. The 8th, 9th and 10th columns depict the percentages of successful prognosis over pathological cases for testing, training and overall data set, respectively. The values in parenthesis exhibit the real number of cases that were detected correctly by implemented MLPs.

The implemented MLPs underwent to further processing in terms of their predicting abilities. As mentioned in section II, the possible stages of osteoporosis examination are four, whereof three are referred in pathological situations and one is referred for patients without osteoporosis. Consequently, the osteoporosis risk factor's stages classified into two groups, one for pathological cases and another group for persons without osteoporosis. These results were encoded to 0 for normal cases and 1 for pathological cases, thus it was attempted a binary coding of the desired results, in order to be used by artificial neural models.

The results of MLPs' simulating phase for two stages coding are summarized in Table IV. In particular, the columns 11^{th} to 13^{th} depicts the percentage of cases that were classified correctly, whereas 14^{th} to 16^{th} columns presents the pathological cases that were detected true positive cases.

During the implemented phase, the initial weights and biases of MLP neural networks were varied, keeping the other parameters unchangeable. In particular, Nr. 1 and Nr. 2 neural network models have the same architecture, but their initial conditions were differed. Similar configurations were applied to Nr. 4 – 7 and Nr. 8 – 10 in order to train and construct ANNs for osteoporosis risk factor prediction. It is obvious that different initial conditions for MLPs training imply variation of neural networks' performance.

The obtained results on Table IV present that as the number of neurons in hidden layer is increased, the improvement of MLPs' performance is achieved. This behavior is prospective, as the more neurons in hidden layer, the more weights and bias, so the MLP's ability is improved to store acquired knowledge. The performance's comparison

of MLPs' 4-3-1 with 4-5-1 topology proves this statement. However, a maximum number of neurons in hidden layer exists, whereas overstepping this number implies the decrement of MLP's performance. The limitation of number of hidden neurons results from overfitting problem, as the neural network has memorized the training patterns, but it has not learnt to generalize to new data [12]. The neural networks from Nr. 2 and Nr. 11 have difficulty in recognizing normal patterns and sorting them in appropriate classification area, as they have not the ability to learn from normal input data.

It is obvious that MLPs' performance with 2-stages osteoporosis coding has been improved, contrary to MLPs that had to classify cases into four stages. For example, Nr. 8 MLP with 2-stages osteoporosis coding outperforms to this with 4-stages. The first MLP had not the ability to discriminate patients without osteoporosis, classifying all records as pathological cases; however, the later MLP classified correctly more cases.

Despite of the correct classification of entire and pathological cases, it is important feature for implemented MLPs the normal cases that were sorted correctly. Specifically, the Nr. 6 MLP has satisfactory results, however, only a small number of the normal cases distinguished rightly. The specific MLP classified correctly 319 patterns, whereof only one pattern belonged to normal class, whereas the remained patterns were pathological cases. Similar behavior is observed for training and overall set, with 4 and 5 normal cases, correspondingly, classified correctly.

This study investigates the implementation of neural network models in order to incorporate in medical decision support systems. The aim of a MLP with 4-5-1 topology, and the utilization of competitive transfer function in hidden layer, is the combination of types, topologies and transfer functions of neural networks in order to construct more efficient neural networks. Nevertheless, the aforementioned MLP presents diminished performance contrary to other MLP's structures. Moreover, it is clear that this MLP have overfitting problem as its ability to distinguish new normal and pathological patterns is inexistent.

The Table V presents the obtained results of PNNs. The radbas and compet were the transfer functions for hidden and output layers, correspondingly. Whereas the number of

TABLE IV
EXPERIMENTAL RESULTS USING MLP

Nr	Architecture of Artificial Neural Network	Transfer Function	Goal MSE	4-Stages Osteoporosis Coding						2-Stages Osteoporosis Coding					
				Percentage of Successful Prognosis			Percentage of Successful Prognosis Over Pathological Situations			Percentage of Successful Prognosis			Percentage of Successful Prognosis Over Pathological Situations		
				Testing Set	Training Set	Overall Set	Testing Set	Training Set	Overall Set	Testing Set	Training Set	Overall Set	Testing Set	Training Set	Overall Set
1	4–3–1	tansig purelin	0.5	29.30 (293)	28.98 (703)	29.07 (996)	34.40 (291)	34.31 (701)	34.33 (992)	83.70 (837)	83.80 (2033)	83.77 (2870)	97.75 (827)	98.43 (2011)	98.23 (2838)
2	4–3–1	tansig purelin	0.5	29.40 (294)	31.12 (755)	30.62 (1049)	34.75 (294)	36.96 (755)	36.31 (1049)	84.90 (849)	83.88 (2035)	84.18 (2884)	99.76 (844)	99.31 (2029)	99.45 (2873)
3	4–3–1	tansig purelin	0.9	31.00 (310)	31.20 (781)	31.84 (1091)	36.64 (310)	38.23 (781)	37.77 (1091)	19.30 (193)	19.21 (466)	19.24 (659)	4.61 (39)	4.16 (85)	4.29 (124)
4	4–5–1	tansig purelin	0.5	31.10 (311)	31.74 (770)	31.55 (1081)	36.76 (311)	37.69 (770)	37.42 (1081)	67.60 (676)	70.20 (1703)	69.44 (2379)	77.66 (657)	81.60 (1667)	80.44 (2324)
5	4–5–1	tansig purelin	0.5	30.70 (307)	30.87 (749)	30.82 (1056)	36.29 (307)	36.56 (747)	36.48 (1054)	81.60 (816)	81.41 (1975)	81.47 (2791)	92.91 (786)	91.48 (1869)	91.90 (2655)
6	4–5–1	tansig purelin	0.5	31.90 (319)	32.40 (786)	32.25 (1105)	37.59 (318)	38.28 (782)	38.08 (1100)	74.20 (742)	73.45 (1782)	73.67 (2524)	84.63 (716)	84.39 (1724)	84.46 (2440)
7	4–5–1	tansig purelin	0.5	32.30 (323)	33.35 (800)	33.04 (1132)	37.59 (318)	38.96 (796)	38.56 (1114)	84.90 (849)	84.30 (2045)	84.47 (2894)	100.00 (846)	99.95 (2042)	99.97 (2888)
8	4–5–1	tansig purelin	0.9	30.70 (307)	30.87 (749)	30.82 (1056)	36.29 (307)	36.56 (747)	36.48 (1054)	81.60 (816)	81.41 (1975)	81.47 (2791)	92.91 (786)	91.48 (1869)	91.90 (2655)
9	4–5–1	tansig purelin	0.9	32.30 (323)	33.35 (809)	33.04 (1132)	37.59 (318)	38.96 (796)	38.56 (1114)	74.20 (742)	73.45 (1782)	73.67 (2524)	84.63 (716)	84.39 (1724)	84.46 (2440)
10	4–5–1	tansig purelin	0.9	31.60 (316)	32.03 (777)	31.90 (1093)	37.00 (313)	37.59 (768)	37.42 (1081)	35.80 (358)	34.00 (825)	34.53 (1183)	31.44 (266)	29.56 (604)	30.11 (870)
11	4–5–1	compet purelin	0.5	29.30 (293)	28.24 (685)	28.55 (978)	34.63 (293)	33.53 (685)	33.85 (978)	68.10 (681)	65.66 (1593)	66.37 (2274)	70.80 (599)	67.99 (1389)	68.81 (1988)
12	4–7–1	tansig purelin	0.5	31.60 (316)	32.03 (777)	31.90 (1093)	37.00 (313)	37.59 (768)	37.42 (1081)	41.60 (416)	45.18 (1096)	44.13 (1512)	44.92 (380)	48.56 (992)	47.49 (1372)

neurons for input and hidden layers of PNNs was constant, the number of output neurons was variable according to the coding of desired values. The spread of radial basis function, which is used in second layer, is the only parameter that can be modified. The values of spread for PNNs with the best performance are presented in the 2nd column of the Table V. Initially, the implementation of PNNs based on the 4-stages of osteoporosis risk factor prediction, so the output layer consisted of 4 neurons. The obtained results of 4-2426-4 PNN topology, after the simulating phase, underwent to similar processing with those of MLPs. Consequently, the 3rd, 4th and 5th columns exhibit the percentage of successful classification of patterns, whereas the 6th, 7th and 8th columns represent the performance of PNNs over pathological patterns for testing, training and overall data set, correspondingly.

Moreover, the desired stages of osteoporosis risk factor were classified into two groups, one for pathological cases and another group for persons without osteoporosis. In this case, the PNN topology was modified, leading the number of neurons for output layer to two. The corresponding results that were obtained by execution of 4-2426-2 PNNs topology are presented in 9th to 14th columns of Table V.

A small variation of radial basis spread does not affect the PNNs' performance, as it is shown by Nr. 1 and Nr. 2 PNNs in Table V. The difference between 0.5 and 0.6 is impalpable, so it does not occurred alteration of obtained results. The increase of spread's value implies the decrease of PNN's performance for estimation of normal and pathological cases for overall and training data set. Moreover, it is mentioned that the percentage of successful prognosis for overall and pathological cases of testing set increases as the spread's value increases. However, there is a value of spread that constitutes limit for the performance improvement for testing set. The limit for spread parameter of the implemented PNNs equals to 7.3, whereas values greater than aforementioned number involves the decrement of PNNs' predicting ability for testing set. The Nr. 1 and Nr. 2 PNNs have not sufficient generalization ability, contrary to Nr. 3 PNN, which classifies correct new patterns that present in the input layer of the neural network.

It is pointed out that Nr. 4 PNN outperforms Nr. 3 PNN, as concluded by obtained results. Nevertheless, it is important the comparison of differences between successful prognosis of entire and pathological cases for testing, training and overall data set. The physical substance of these differences is the number of normal cases that classified correctly. Thus, the successful categorized normal cases are 14, 67 and 81 for testing, training and overall data of Nr. 3 PNN, whereas for Nr. 4 PNN corresponding values are 10, 26, and 36. It is obvious that Nr. 3 PNN have the ability to classify more normal cases that Nr. 4 PNN. Consequently, Nr. 3 PNN outperforms Nr. 4 PNN, in terms of generalization ability. Nr. 3 PNN distinguishes satisfactory the pathological patients as normal cases, namely, it is resulted to increase its prognostic ability, whereas at the same time its performance is a little diminished contrary to Nr. 4 PNN.

TABLE V
EXPERIMENTAL RESULTS USING PNN ARCHITECTURES

Nr	Spread of radbas	4 neurons for output layer						2 neurons for output layer					
		Percentage of Successful Prognosis			Percentage of Successful Prognosis Over Pathological Situations			Percentage of Successful Prognosis			Percentage of Successful Prognosis Over Pathological Situations		
		Testing Set	Training Set	Overall Set	Testing Set	Training Set	Overall Set	Testing Set	Training Set	Overall Set	Testing Set	Training Set	Overall Set
1	0.5	30.40 (304)	99.04 (2233)	74.05 (2537)	32.74 (277)	93.10 (1902)	75.42 (2179)	78.80 (788)	97.28 (2360)	91.89 (3148)	89.95 (761)	99.51 (2033)	96.71 (2794)
2	0.6	30.40 (304)	99.04 (2233)	74.05 (2537)	32.74 (277)	93.10 (1902)	75.42 (2179)	78.80 (788)	97.28 (2360)	91.89 (3148)	89.95 (761)	99.51 (2033)	96.71 (2794)
3	2.7	34.80 (348)	58.16 (1411)	51.34 (1759)	38.42 (325)	61.58 (1258)	54.79 (1583)	84.70 (847)	86.73 (2104)	86.14 (2951)	98.46 (833)	99.70 (2037)	99.34 (2870)
4	3.6	36.20 (362)	50.62 (1228)	46.41 (1590)	40.67 (344)	54.19 (1107)	50.22 (1451)	85.00 (850)	85.20 (2067)	85.14 (2917)	99.29 (840)	99.90 (2041)	99.72 (2881)
5	7.3	40.30 (403)	41.63 (1010)	41.24 (1413)	46.10 (390)	48.21 (985)	47.59 (1375)	84.80 (848)	84.46 (2049)	84.56 (2897)	99.88 (845)	100.00 (2043)	99.97 (2888)
6	13.1	38.20 (382)	39.74 (964)	39.29 (1346)	44.92 (380)	46.84 (957)	46.28 (1337)	84.70 (847)	84.21 (2043)	84.35 (2890)	100.00 (846)	100.00 (2043)	100.00 (2889)
7	19.2	37.50 (375)	38.13 (925)	37.95 (1300)	44.21 (374)	45.28 (925)	44.96 (1299)	84.60 (846)	84.21 (2043)	84.33 (2889)	100.00 (846)	100.00 (2043)	100.00 (2889)
8	40.0	32.10 (321)	32.28 (783)	32.22 (1104)	37.94 (321)	38.26 (783)	38.21 (1104)	84.60 (846)	84.21 (2043)	84.33 (2889)	100.00 (846)	100.00 (2043)	100.00 (2889)

IV. CONCLUSION

ANNs, as a subfield of computational intelligence, are used widely in industrial and medical applications. Despite of the ANN's architectures, learning algorithms and transfer functions variety, the basic function of ANNs is the presence of an input data set, and the generation of corresponding outputs based on vector mapping.

In this paper, the possibility of applying artificial neural models in medical making decision, and in particular, the osteoporosis risk factor estimation has been examined, because it is an important medical problem for public health. Its frequency and the serious consequences for patients are the reasons for the vivid interesting for development of accurate and timeous techniques which do not expose the patients in radiation.

The development of artificial neural techniques was based on MLPs with back-propagation algorithm, as well as PNNs, which are both feed-forward neural networks. The MLPs has been characterized as black box, because the internal connections are highly non-linear and not subject to the usual statistics. On the other hand, PNNs approximate Bayesian function; however, their output is clearly not a probability, as several steps are required to osteoporosis risk factor prediction.

As it was found, the PNNs outperformed the MLPs, in terms of the successful prognosis of cases. Therefore the proposed methodology unveiled the PNN artificial models' behavior contrary to MLPs artificial networks' behavior is much better, or in other words, the prognostic ability of PNNs is enhanced compared to MLPs categorization performance.

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