The use of artificial intelligence techniques for the Diagnosis of periodontal disease by clinical indices

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Abstract

Periodontal diseases are of the common oral infectious diseases that early diagnosis is very important. This study aims to evaluate the artificial neural network role in the periodontal disease diagnosis. The Diagnostic Study were performed from periodontal disease cases in Zahedan Dentistry School in the period of time between 2015 and 2016. Clinical Indices were evaluated in these people. The feed forward artificial neural network model with propagation algorithm of Levenberg-Marquardet training function was used. Periodontal patients were divided into two groups of train (160 people), and test (30 people). The results showed that Levenberg-Marquardet algorithm with fewer iterations and a minimum mean square error and low time can used to diagnosis of periodontal disease. Therefore, artificial neural network is a good tool for diagnosing a periodontal disease

Keywords

Artificial intelligence techniques, clinical indices, oral diseases

1. Background

Artificial neural networks are inspired by the biological neural system and its ability to learn through example [1]. Mathematical models based on artificial intelligence now serve in support of certain diagnoses [2-4]. Neural networks have the capacity to "learn" how to make a diagnosis through the information presented to them [5-8]. The history of neural networks dates backs to the mid-20th century. The neural networks may seem complicated at first, but they can be easily merged with a medical environment [9]. Today, due to the development of knowledge in the medical field as well as complexity of the decisions related to diagnosis and treatment, specialists pay attention to smart tools and decision support systems in medical issues, and the use of different kinds of smart systems in medicine has been increasing [10,11]. Using these tools and systems can decrease the potential errors that may arise due to the medical specialists' tiredness or their inexperience in the diagnosis and treatment of diseases. In addition, by using these systems, we can analyze the medical database in much less time and in more detail [10-12]. So, for this purpose, we must use the models that have minimum errors and maximum confidence. Oz den et al. (2014), in their study titled "Periodontal disease diagnosis using classification algorithms," found that the decision tree and supporting vector machine with high precision were suitable for periodontal disease classification [13]. In 2012, a study conducted by Kositbowornhcahi et al., titled "The neural network function for diagnosing vertical fracture of tooth root," found that the neural network designed for their research had high insensitivity, accuracy and verity in vertical tooth root diagnosis [14]. In 2008, in their study titled "The multilayer perceptron neural network for diagnosis of proximal plaque," DeVito et al. reported that according to specialists, there was an improvement of 39.5% in diagnosis [15]. Martina et al. (2006) showed that neural network can be used as an important tool for improving medical behaviors and maximizing the profit of treatment costs [16]. In a study titled "Estimation of dental ceramics chemical resistance using neural network," Zivco Babic et al. (2008) reported that artificial neural network has high potential as an additional method in investigating the properties of dental materials [17]. In 2013, Amiri et al.'s study titled "Determining the effect of qualitative and quantitative prediction of survival of patients with gastric cancer using hierarchical neural network models," concluded that compared to Cox model, neural network can accurately anticipate the probability of survival of patients with gastric cancer [18]. Shankarapillai et al. (2012) showed that natural network trained by Levenberg-Marquardet algorithm can be used effectively in diagnoses of periodontal disease risk [19]. Moghimi et al. (2012) conducted a study titled "Designing and using a combination of genetic algorithm and artificial neural network for anticipating the size of hidden canines and premolar size," which showed that the proposed method was an efficient tool for

anticipating the size of hidden canines and premolar with high accuracy in comparison to regression analysis [20]. According to the previous studies, it can be said that the unique capability of artificial neural networks to differentiate, categorize and diagnose diseases can be efficient and useful [21].

Periodontitis is a common inflammatory disease [22] in humans, and its main cause is long-term bacterial infection [23]. Research on the pathobiology of periodontal disease increases our knowledge of this disease [24].

Artificial neural network

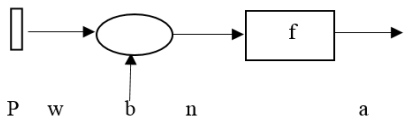
Each artificial neural network is made of input, hidden and output layers. There are some processing elements (neurons and nodes) in each layer. A neural network is a set of processors in which each processor is associated with the processor in the next layer. The relations between the network layers are possible according to weight coefficients and bias of each processor and the threshold and transfer functions. Finally, the network output can be regarded as the simulated value resulting from the training network. While training the network, it is necessary to minimize the network simulation error by choosing a suitable learning algorithm. In the back propagation error method, the main goal is to reduce the network error rate [25]. In this study, we used multilayer feed forward neural network with Levenberg-Marquardet algorithms and three major factors of disease diagnosis: probing pocket depth, clinical attachment loss, and plaque index, to diagnose periodontal disease, and the results of the algorithm were studied.

2. Objectives: This study aims to introduce a model for periodontal disease diagnosis using artificial neural network. In this study, Levenberg-Marquardet algorithm were used.

3. Materials and Methods

In this study, a neural network was designed that diagnosed periodontal disease according to the input variables. The system was evaluated by using a data set related to patients with periodontal disease in the periodontics department of Zahedan Dentistry University in the period between 2014 and 2015. The features and functions available in Matlab software version 2015 were used for network implementation. According to the specialist, the input variables introduced were age, sex, probing pocket depth, clinical attachment loss, and plaque index. The overall structure of the artificial neural network was inspired by the human biological neural network, and is a simplified model of the central neural system. As an information processing system, the brain is composed of structural main elements named neurons. A set of related neurons comprise tissues called nerves, which transfer information and messages from one point to the other in the body. Artificial neural networks include a set of connected neurons each of which is called a layer [26]. Figure 1 shows a single-input neuron structure in which **p** and **a** are the neuron input and output, respectively.

Figure 1. Single-input neuron model



The effect of **p** on **a** is determined by **w** value. Another input is the constant value of 1 which is multiplied by **b** italic sentence and then summed with **WP.** The sum is the n net input for conversion or activation (motive) function of **f.** So, the neuron output is defined as Eq. (1):

$$a = f(WP + b) \qquad (1)$$

Where, parameters **w** and **b** are adjustable, and the motive function of **f** is determined by the designer. The parameters **w** and **b** are set according to the selection of **f** and the type of learning algorithm. In fact, learning means that **w** and **b** change so that the relation of neuron input and output are set with a special goal. Finally, the neurons are attached by the activation (motive) functions to create layers [19]. Despite their diversity, the artificial neural networks have similar structures [26]. A neural network is usually composed of three layers: input, hidden, and output [27]. The input layer only receives the information and acts as an independent variable, and therefore, the number of neurons in the input layer is determined on the basis of the problem's nature. The output layer acts as a dependent variable, and the number of its neurons depends on the number of independent variables; but unlike the input and output layers, the hidden layer shows no meaning and is just an intermediate result in the process of calculating the output value [28]. Feed forward neural networks are the most applied type of artificial neural networks [26], because the feed forward neural networks, with one hidden layer, logistic activation function in the hidden layer, linear activation function in the output layer, and enough neurons in the hidden layer, can approximate any function with arbitrary accuracy [27]. For this reason, this kind of neural network with the above structure is called comprehensive approximation. It means that by having enough numbers of hidden units and suitable numbers of neurons in this layer, the network can almost approximate every linear and nonlinear function with an arbitrary accuracy level [28]. Accordingly, a feed forward neural network has been used in this study. Data should be divided into two different sets of train and test samples for designing and training an artificial neural network, because it is necessary to use train and test data for network design [29]. Train sample is a set of network inputs and outputs that is used for training a special work to the network. After network training and learning procedure stop, the test sample is used for investigating the network efficiency [28]. Most researchers select the train and test samples with either one of the rules of 90% against 10%, 80% against 20%, or 70% against 30% [30]. Naturally, the selection of any rule depends on the problem type. But different researches have indicated that increasing the number of train samples improves the network operation in the field of anticipation [29]. In this study, about 80% of data was used as train

sample and 20% of data as test sample. For training, were used during the design phase in the data related to 160 patients (train). The 30 remaining data were used to simulate neural network models for each of the algorithms (test) applied. The input variables (factors) for periodontal disease diagnosis were investigated in all the 190 patients, as is evident in Table 1. The data were imported to the Matlab software as input values. Periodontal disease diagnosis on each patient's record was made in 1-4 interval by one specialist, so that target parameter 1 was regarded for the values of attachment loss index that were between 1 and 2; target parameter 2 for the values of attachment loss index in 2 and 3 intervals, target parameter 3 for the values between 3 and 4, and target parameter 4 for the values between 4 and 5. Therefore, 40 data were considered with target parameter 1, 40 data with target parameter 2, 40 data with target parameter 3, and 40 data with target parameter 4 for the train phase. The 30 remaining data including seven data with target parameter 1, seven data with target parameter 2, eight data with target parameter 3, and eight data with target parameter 4 were considered. The mean square error and regression parameters with maximal 1000 epoch were considered for the two algorithms. Descending slope with momentum weight and bias learning function and mean square error function were used for Levenberg-Marquardet algorithms. The Sigmoid transfer function was selected for both layers. The Levenberg-Marquardet algorithm was trained with 1000 epochs and minimum tangent of 1e-010 and infinite time First, 160 samples were trained for designing the natural network by Levenberg-Marquardet algorithm. The outputs of both the trained networks were saved, and the results were compared for determining the most efficient algorithm for periodontal disease diagnosis.

Table 1. Factors of periodontal disease diagnosis and their values range as input parameters

Factors	The range of values
Age	18–55
Sex	Female/male
Probing Pocket Depth	(1–4)
Clinical Attachment Loss	(0–4)
Plaque Index	0–100%

4. Results

The Matlab programming environment version 2015 was used to implement the algorithms. An artificial neural network modeling process was performed by a set of training data. First, 160 samples were used to train the neural network for both the Levenberg-Marquardet algorithms, and then 30 remaining

samples were used to test the neural network. By fitting different artificial neural networks, a model was designed with two hidden layers, 20 neurons in the first hidden layer, 4 neurons in the second hidden layer and 5 neurons are output (5-20-4-4). Table 2 shows the designed neural network output after the implementation of the multilayer perceptron neural network in the Matlab software by the Levenberg-Marquardet algorithms. The train phase for the Levenberg-Marquardet algorithm was performed in 6.5870 seconds with six validations in 16 iterations. The rates of regression for train, validation, and test phase were computed as 0.9649, 0.8687, and 0.7354, respectively. The compound regression for the three phases of train, validation, and test was computed as 0.9054. The optimal Gradient in this study was 0.0012. In the present study, the best performance of error validation in the Levenberg-Marquardet algorithms in periodontal disease diagnosis indicated that the Levenberg-Marquardet algorithm training in 22 performances gained 0.0098 for mean square error; there by showing that the Levenberg-Marquardet algorithm has a best performance in error management. The numbers of iterations for the Levenberg-Marquardet algorithm were 16, so the algorithm arrived with low iterations. According to the results,. The Levenberg-Marquardet algorithms were performed in 6.5870 seconds, respectively, indicating that the Levenberg- Marquardet algorithm performed soon. Among the three factors of error management, number of iterations and time, the Levenberg-Marquardet algorithm was best in the three factors. Therefore, in a situation in which it is impossible to access periodontics specialist idea, due to negligible time difference and low error, we can use the Levenberg-Marquardet algorithm for periodontal disease diagnosis.

Table 2. The results for LM algorithms

Neural Network Algorithms	Levenberg Marquardt
Time Executed (in Seconds)	6.5870
Epochs Run	22
Convergence Iteration	16
Best Performance (MSE)	0.0098
Optimal Gradient	0.0012
R Value Training	0.9649
R Value Validation	0.8687
R Value Test	0.7354
Overall R Value	0.9054

5. Discussion

This study aims to develop a diagnosis system by artificial neural network for periodontal disease diagnosis. Age, sex, probing pocket depth, clinical attachment loss, and plaque index were selected as

the main variables in neural network learning. Artificial neural networks have been used to help physicians in diseases diagnosis for the past five decades. Previous studies have demonstrated that artificial neural network accuracy was an important tool for diagnosis of diseases, but we didn't find any research in the field of diagnosis in the area of oral and dental diseases by neural network in Iran.

Also, according to the searches done by authors of this study, all the diagnostic research used in the field of oral and dental diseases were used by the statistical test. Therefore this study is important from this perspective. A small number of foreign studies have used artificial neural network for the diagnosis of oral and dental disease, some of which were mentioned in the introduction. This shows the importance of the study in this field. As the results showed, the neural network designed by the Levenberg-Marquardet algorithm can be used with low time, low error and low iteration can be used in the diagnosis of periodontal disease by dentists.

References

1. ISO 6872. International standards for dental ceramics. Geneva, Switzerland: International Organization for Standardization; 1995.
2. Bishop, CM. Neural networks for pattern recognition. New York: Oxford University Press, p. 482, 1995.
3. Brickley, MR, Shepherd, JP, Armstrong, RA. Neural networks: a new technique for development of decision support systems in dentistry. *J Dent*, No.26, pp. 305-309, 1998.
4. Brickley, MR, Shepherd, JP. Comparisons of the abilities of a neural network and three consultant oral surgeons to make decisions about third molar removal. *Br Dent J*, No. 182, pp. 59-63, 1997.
5. Bains, R, Turner, DW, Greener, EH. Comparison of statistical and neural network analysis of periodontal data. *Northwest Dent Res*, No.4, pp. 2-3, 1994.
6. Speight, PM, Elliott, AE, Julien, JA, Downer, MC, Zakzrewska, JM. The use of artificial intelligence to identify people at risk of oral cancer and pre-cancer. *Br Dent J*, No. 179, pp.382-7, 1995.
7. Brickley, MR, Shepherd, JP. Performance of a neural network trained to make third-molar treatment-planning decisions. *Med Decis Making*, No. 16, pp.153-60, 1996.
8. Goodey, RD, Brickley, MR, Hill, CM, Shepherd, JP. A controlled trial of three referral methods for patients with third molars. *Br Dent J*. No. 189, pp. 556-60, 2000.
9. Livingstone, DJ, Artificial Neural Networks: Methods and Applications (Methods in Molecular Biology), Humana Press, 2008 Oct 8.
10. Shankarapillai, R, Mathur, LK, Nair, MA, George, R. Periodontitis risk assessment using two artificial neural network algorithms–a comparative study. *International Journal of Dental Clinics*, Vol.4, No. 1, 2013.

11. Milovic, B, Milovic, M, Prediction and decision making in health care using data mining. *Kuwait Chapter of the Arabian Journal of Business and Management Review*, 2012.
12. Sheikh pour, R, Sarram, MA. Diagnosis of Diabetes Using an Intelligent Approach Based on Bi-Level Dimensionality Reduction and Classification Algorithms. *Iranian Journal of Diabetes and Obesity*, Vol.6, No. 2, pp. 74-84, 2014.
13. Oz den, FO, Ozgonenel, O, Oz den, B, Aydogdu, A. Diagnosis of periodontal diseases using different classification algorithms: A preliminary study. *Nigerian journal of clinical practice*, Vol. 18, No. 3, pp. 416-421. 2015.
14. Kositbowornchai, S, Plermkamon, S, Tangkosol, T. Performance of an artificial neural network for vertical root fracture detection: an ex vivo study, *Dental traumatology*, Vol.29, No. 2, pp. 151-155, 2012.
15. DeVito, KL, de Souza Barbosa, F, Felippe Filho, WN, An artificial multilayer perceptron neural network for diagnosis of proximal dental caries. *Oral Surgery, Oral Medicine, Oral Pathology, Oral Radiology, and Endodontology*, Vol. 106, No. 6, pp. 879-84, 2008.
16. Martina, R, Teti, R, Addona, DD, Iodice, G. Neural network based system for decision making support in orthodontic extractions, *Intelligent Production Machines and Systems*. pp. 235-40, 2006.
17. Živko-Babić, J, Lisjak, D, Ćurković, L, Jakovac, M. Estimation of chemical resistance of dental ceramics by neural network. *Dental materials*, Vol. 24, No. 1, pp. 18-27, 2008.
18. Amiri, Z, Mohammad, K, Mahmoudi, M, Parsaeian, M, Zeraati, H. Assessing the effect of quantitative and qualitative predictors on gastric cancer individuals survival using hierarchical artificial neural network models, *Iranian Red Crescent Medical Journal*, Vol.15, No. 1, pp. 42, 2013.
19. Shankarapillai, R, Mathur, LK, Nair, MA, George, R. Periodontitis risk assessment using two artificial neural network algorithms–a comparative study, International Journal of Dental Clinics, Vol.4, No. 1, 2012.
20. Moghimi, S, Talebi, M, Parisay, I. Design and implementation of a hybrid genetic algorithm and artificial neural network system for predicting the sizes of unerupted canines and premolars, *The European Journal of Orthodontics*, Vol.34, No. 4, pp. 480-486, 2012.
21. Thohamtan, RA, Esmaeili, MH, Ghaemian, A, Esmaeili, J, Application of Artificial Neural Network for Assessing Coronary Artery Disease, *Journal of Mazandaran University of Medical Sciences (JMUMS)*, Vol. 22, No. 86, 2012.
22. Moghaddam SA, Abbasi S, Moghaddam ES, Moghaddam AA. Triglyceride and cholesterol levels in patients with chronic periodontitis. *Health Scope*. 2015;4(2).

23. Ainamo, J, Ainamo, A. Risk assessment of recurrence of disease during supportive periodontal care, *Journal of clinical periodontology*, Vol. 23, No. 3, pp. 232-239, 1996.
24. Page, RC, Krall, EA, Martin, J, MANCL, L, Garcia, RI. Validity and accuracy of a risk calculator in predicting periodontal disease, *The Journal of the American Dental Association*, Vol. 133, No. 5, pp. 569-576, 2002.
25. Zounemat Kermani, M, Bay, YM, Efficiency Analysis of Artificial Neural Network and Multiple Liner Regression Methods For Tides Prediction, *The Journal of Oceanography*, Vol. 13, No. 4, pp. 1-10, 2013.
26. Menhaj, MB, Fundamentals of neural networks, Computational intelligence, 1998.
27. Kuan, CM, White, H, Artificial neural networks: an econometric perspective∗. Econometric reviews, Vol. 13, No. 1, pp. 91, 1994.
28. T Honar, T, Tarazkar, MH, Tarazkar, MR, Estimating of Side Weir Discharge Coefficient by Using Neuro-Fuzzy (ANFIS).
29. Zhang, G, Patuwo, BE, Hu, MY, Forecasting with artificial neural networks: The state of the art, *International journal of forecasting*, Vol.14, No.1, pp. 35-62, 1998.
30. Hoo, KA, Sinzinger, ED, Piovoso, MJ, Improvements in the predictive capability of neural networks. *Journal of Process Control*, Vol. 12, No. 1, pp. 193-202.

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