Diagnosis of periodontal diseases using different classification algorithms: A preliminary study

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Abstract

Objective: The purpose of the proposed study was to develop an identification unit for classifying periodontal diseases using support vector machine (SVM), decision tree (DT), and artificial neural networks (ANNs).

Materials and Methods: A total of 150 patients was divided into two groups such as training (100) and testing (50). The codes created for risk factors, periodontal data, and radiographically bone loss were formed as a matrix structure and regarded as inputs for the classification unit. A total of six periodontal conditions was the outputs of the classification unit. The accuracy of the suggested methods was compared according to their resolution and working time.

Results: DT and SVM were best to classify the periodontal diseases with a high accuracy according to the clinical research based on 150 patients. The performances of SVM and DT were found 98% with total computational time of 19.91 and 7.00 s, respectively. ANN had the worst correlation between input and output variable, and its performance was calculated as 46%.

Conclusions: SVM and DT appeared to be sufficiently complex to reflect all the factors associated with the periodontal status, simple enough to be understandable and practical as a decision-making aid for prediction of periodontal disease.

Key words: Algorithm, artificial neural networks, decision tree, periodontal disease, support vector machine

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Introduction

Periodontal diseases are among the most common chronic diseases to affect adults and is one of the main causes of tooth loss in adults.[1] Traditionally, diagnosis of a periodontal disease is made by the clinical signs and symptoms together with the medical history of the patient and may be supported radiographically. Once the disease is diagnosed and classified, it is possible to organize the effective treatment. However, the problem is that the decision of the clinician may be subjective, and there may be mistakes in dental practicians and students for diagnosis.

In the presented study, the classification and identification of the periodontal diseases were achieved by three significant classifiers such as artificial neural networks (ANNs), support vector machine (SVM), and decision tree (DT). Biologically inspired ANNs are designed to simulate the way in which the human brain processes information. It is consisted of hundreds of single units, artificial neurons, connected with coefficients which constitute the neural structure.[2] ANNs was designed to stimulate the function of the biologically neuron, inputs are first combined and then passed through a transfer function to produce one output. The application of ANN has been reported to show great potential as a support system and management system in medical decision-making[3] and were used in the prediction, classification, function estimation, pattern, recognition, and completion problems in many disciplines, including medicine.[4] SVM is a supervised learning method that produces input-output mapping

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functions from training data and DT learning is one of the most broadly used and handy methods for inductive assumption. It is a method for approximating discrete-valued functions that is robust to noisy data and capable of learning disjunctive expressions.[5] SVM has been previously used for preoperative prediction of advanced prostatic cancers[6] and tumor marker detection for different types of cancers.[7,8] ANNs, DT, and SVM were also compared with each other and performed for prediction models.[9]

Although there are a few studies in dental area with the use of ANNs[10-12] and SVM,[13] there exist no available data for diagnosing and classification of periodontal diseases with the use of different types of algorithms alone or that compare the differences between each other.

To our knowledge, it is the first time that three classification algorithms known as ANN, SVM, and DT were tested to diagnose periodontal diseases and compare the performances of the proposed algorithms for periodontal diseases with the diagnosis of a specialist.

Materials and Methods

Study population

Data were randomly collected from 150 patients who referred for periodontal therapy from December 2011 until February 2012. This study was approved by the Clinical Research Ethics Board of School of Medicine, Ondokuz Mayıs University. 100 patients were evaluated by an experienced periodontist and used as input variables. Final diagnosis (the outputs) was made by considering patients' medical histories, clinical signs, and symptoms together with radiographical findings and achieved by another 50 patients. A total of 11 variables was used for defining input conditions. Gender, age, education, smoking, gingival index (GI) of Löe and Silness,[14] plaque index (PI) of Silness and Löe,[15] probing pocket depth (PD), clinical attachment level (CAL), gingival recession (GR), bleeding on probing (BOP),[16] and radiographically bone loss (RBL) were evaluated and coded numerically for the input matrix. The outputs were grouped as healthy, gingivitis, localized chronic periodontitis (LCP), generalized chronic periodontitis (GCP), localized aggressive periodontitis (LAP), and generalized aggressive periodontitis (GAP).

Gender, education status, smoking, BOP, RBL, and diagnosis were coded; the other parameters were evaluated as they were measured. One value was given to the male patients and two for the female patients. 1–5 scores for numbering the categories from primary school to postgraduation were given in order to code education status. For coding smoking; smokers were coded as one and two; for nonsmokers [Table 1]. All the parameters that can easily be obtained by practitioners were represented as numerical codings for classification algorithms.

Clinical periodontal measurements

The periodontal status of the subjects was identified by measuring; GI,[14] PI,[15] BOP, PD, CAL, GR, and alveolar bone loss, orthopanthomographically. All clinical parameters were measured at six sites (mesial, median and distal points at buccal and palatal aspects) and divided by six to give a tooth score and then all tooth scores were divided by total examined number of teeth, except third molars. PI, GI, BOP, PD, GR, and CAL were recorded with using a periodontal probe. All clinical and radiographical examinations were carried out by an experienced periodontist (FOÖ) from the Periodontology Department.

Gingival recession, as the distance between the cement-enamel junction (CEJ) to the gingival margin, was calculated for each patient. CAL, defined as the distance between implant shoulder/CEJ and periimplant/periodontal pocket base was measured and computed from the GR and PD measurements.

Alveolar bone loss was evaluated orthopantomographically and coded as 1 = no alveolar bone loss, 2 = alveolar bone loss affected in ≤30 of all sites, 3 = alveolar bone loss affected in ≥30 of all sites.

Periodontal assessments for the training and the test groups are shown in Table 2.

Patients were diagnosed according to criteria described by the American Academy of Periodontology.[17] Cases were categorized and coded numerically for the system as:

1. Healthy; The individuals demonstrating GI = 0, no BOP, and PD and CAL <3 mm without alveolar

Table 1: Number of patients and codings created for demographic factors

Parameter (*n* (%))	Training group (*n*=100) (%)	Test group (*n*=50) (%)
Gender		
1	45 (45)	28 (56)
2	55 (55)	22 (44)
Education		
1	13 (13)	-
2	15 (15)	7 (14)
3	42 (42)	28 (56)
4	27 (27)	15 (30)
5	3 (3)	-
Smoking		
1	34 (34)	27 (54)
2	66 (66)	23 (46)

*For gender: 1 and 2, education: 1-5, smoking: 1 and 2 codings were applied for the algorithms bone loss were accepted as the periodontally healthy patients

2. Gingivitis; presence of BOP, (CAL) <1 mm, (PD) ≤3 mm, (GI) <1, had no clinical signs of periodontitis.

The diagnosis of periodontitis was based almost entirely on traditional clinical and radiographic assessments.[18] To be eligible for inclusion, participants had to have a clinical diagnosis according to the American Academy of Periodontology criteria, with a ≥1 mm mean CAL, sites with PD ≥4, with BOP and/or suppuration and radiographic evidence of bone loss, including slight, moderate, and severe periodontitis.[17]

3. LCP; up to 30% of sites in the mouth are affected
4. GCP; >30% sites with radiographic evidence of bone loss.

The diagnosis of aggressive periodontitis was made on the basis of clinical and radiographic assessment using the classification workshop criteria[17] and the specific characteristic radiographic appearance of aggressive periodontitis.

5. LAP; good health; involvement of more than one first molar; radiographic evidence of alveolar bone loss ≥2 mm on more than one surface of the permanent tooth involved; probing depth at diseased sites >5 mm; and extensive bone loss with respect to the low levels of plaque and calculus unlike typically observed in chronic periodontitis
6. GAP; radiographic evidence of bone loss in more than two sites besides the molars and incisors was considered GAP.

Table 3 presents the number of patients in the training and the test group who were diagnosed and coded numerically.

Table 2: Periodontal parameters for the groups

Clinical parameter	Training group (n=100)	Test group (n=50)
PI (mean±SD (minimum-maximum))	1.5±0.5 (0.4-3.0)	1.5±0.4 (0.4-2.2)
GI (mean±SD (minimum-maximum))	1.3±0.5 (0-3.0)	1.4±0.4 (0.5-2.4)
PD (mm) (mean±SD (minimum-maximum))	1.9±0.5 (1.1-4.1)	2.0±0.5 (1.1-3.4)
CAL (mm) (mean±SD (minimum-maximum))	2.2±0.9 (1.1-4.8)	2.3±0.8 (1.1-4.2)
GR (mm) (mean±SD (minimum-maximum))	0.3±0.4 (0-2.1)	0.3±0.3 (0-1.2)
BOP* (*n* (%))		
1	48 (48)	26 (52)
2	22 (22)	9 (18)
3	30 (30)	15 (30)
RBL* (*n* (%))		
1	54 (54)	26 (52)
2	15 (15)	9 (18)
3	31 (31)	15 (30)

*Number and percentage of patients included in three codings for BOP and RBL. BOP=Bleeding on probing; RBL=Radiographically bone loss; PI=Plaque index; GI=Gingival index; PD=Pocket depth; CAL=Clinical attachment level; GR=Gingival recession; SD=Standard deviation

Table 3: Number of patients and codings numerically created for the groups

Groups (*n* (%))	Diagnosis*						Total
	1	2	3	4	5	6	
Training group	21 (21)	33 (33)	14 (14)	23 (23)	1 (1)	8 (8)	100
Test group	6 (12)	20 (40)	9 (18)	10 (20)	0	5 (10)	50

*Codings for existing periodontal diseases: 1=Healthy; 2=Gingivitis; 3=Localized chronic periodontitis; 4=Generalized chronic periodontitis; 5=Localized aggressive periodontitis; 6=Generalized aggressive periodontitis[17]

Identification and classification procedures

The clinical symptoms, indices, and diagnosis of the first 100 patients were considered the gold standard and were used in training of ANN, SVM, and DT. After the training process, values of 50 new patients were used to verify the classifiers' ability to diagnose the periodontal diseases.

Artificial neural network

Numerous applications of ANN have been successfully conducted to solve engineering problems since it is reliable and robust in capturing the nonlinear relationships existing between variables (multi-input/output) in complex systems.[19] The proposed network type used is a back-propagation neural network (BPNN). BPNN consists of three layers named input, hidden, and output. Input layer receives the information from the outside world. The information obtained from 100 patients was then converted in matrix form of 100 × 12 and used in the input layer for the training procedure. The output layer was formed as 100 × 1 matrix. Additional data obtained from 50 patients were used for testing and validating the performance of the proposed BPNN architecture. Input layer consisted of 11 neurons in this particular example. Sigmoid transfer function was recommended for obtaining activation signals for input and hidden layers. The output layer used linear transfer function for the final decision. Mean square error was used as a criterion during the training procedure.

Support vector machine

The SVM uses the principles of statistical learning theory to find a functional as simple as possible to reach a generalization as good as possible for the description of a given data set.[20] Although SVM separates the data only into two classes, classification into additional classes is possible by applying either the one against all or one against one (OAO) methods. The proposed method uses OAO that constructs parallel SVMs where each SVM is trained on the data from two classes.[21]

Decision tree (C4.5)

A DT is a popular classification method. The most important feature of DT classifier is their ability to break down a complex decision-making process into a complexion of a simpler decision, thus providing a solution which is often easier to interpret. DTs are able to generate understandable rules, perform classification without requiring much computation, are able both handle to continuous and categorical variables and provide a clear indication of which fields are most important for classification. C4.5 DT learning, which was used in this study, is one of the most widely used and practical methods for inductive inference. It is a method for approximating discrete-valued functions that is robust to noisy data and capable of learning disjunctive expressions.[22,23]

Results

Demographic factors, periodontal findings, and the number of patients who were clinically diagnosed in both training and the test group are presented in Tables 1-3. This work was based on the data for a total of 150 patients (73 males and 77 females, aged between 13 and 64 years with an average and standard deviation of 31.56 ± 12.3 years). The data belonging to 100 patients (mean age, 30.54 ± 12.57) were used for the training procedure of ANNs, SVM, and DT. The rest (mean age; 33.62 ± 12.43) was chosen for testing procedure.

During the testing procedure ANN was constructed as 11 neurons for the input layer, 11 neurons for the hidden layer, and one neuron for the output layer. The input and hidden layer used the sigmoid type activation while the output layer used linear activation neuron. In SVM, RBF-based kernel function was used and in DT MCBagging algorithm was used as the kernel function. As stated above, ANN had one output neuron representing diagnostics labeled 1–6. However, both SVM and DT had six domains each representing different diagnostics. ANN presented the worse results than the SVM and DT. The performances of SVM and DT on the test data were almost the same. The correlation coefficient was calculated as 0.4601 (sensitivity 46%) with a standard deviation of 1.551 and maximum error of 3.992 in ANN. Figure 1 shows the associated errors during ANN testing.

According to DT, it was concluded that number 1, 2, 3, 4, and 5 diagnostics were identified accurately but only 1 diagnostic out of 5 was identified as diagnostic 4 in the sixth group. This yielded to error of 2%, precision of 98%. Total computational time for DT was 7.00 s. Similarly, according to SVM, it was concluded that number 1, 2, 3, 4, and 5 diagnostics were identified accurately but only 1 diagnostic out of 4 was identified as diagnostic 4 in the sixth group. This yielded to error of 2%, precision of 98%. Total computational time for SVM was 19.91 s. Tables 4 and 5 show the performances of DT and SVM methods.

Table 4: Performance of DT method (MCBagging)

Diagnostics	1	2	3	4	5	6
1	6	0	0	0	0	0
2	0	20	0	0	0	0
3	0	0	9	0	0	0
4	0	0	0	10	0	1
5	0	0	0	0	0	0
6	0	0	0	0	0	4

For DT; Error=0.02, Precisio *n*=0.98, Time=7.00 s. DT=Decision tree

Table 5: Performance of SVM method (sigma=0.1)

Diagnostics	1	2	3	4	5	6
1	6	0	0	0	0	0
2	0	20	0	0	0	0
3	0	0	9	0	0	0
4	0	0	0	10	0	1
5	0	0	0	0	0	0
6	0	0	0	0	0	4

For SVM; Error=0.02, Precisio n=0.98, Time=19.91 s. SVM=Support vector machine

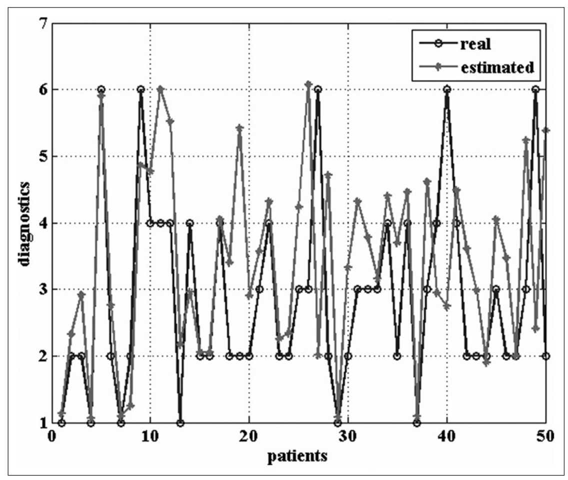

Figure 1: Associated errors during testing data for artificial neural network

Discussion

The purpose of this study was first to train three different algorithms including ANNs, SVM and DT to diagnose periodontal diseases in 100 patients, then predict and compare the practicability by evaluating the data of other 50 patients. The results of this study revealed that SVM and DT algorithms might effectively be used for classification for periodontal diseases.

There is a growing interest to decision systems in medicine nowadays, and they were especially used to predict or classify cancers. Tumor marker detection for different types of cancers was evaluated for the accuracy of diagnostic classifiers such as combined diagnosis test, logistic regression, DT, and SVM. The accuracy of SVM classifier was found to be higher in four kinds of classifiers, and SVM was indicated to be a valuable diagnostic model with tumor marker in cancer detection.[7] In an attempt to identify metastasis-related genes in colorectal cancer, SVM-T-RFE, was trained for gene expression profiles and found to be high in accuracy.[8] The performance of SVM was reported to be superior to ANN in the preoperative prediction of advanced prostatic cancers[6] and was found superior to the linear model in preoperative risk stratification with myocardial perfusion scintigrapy.[24] Kim *et al*.[9] developed a critical care mortality prediction model by comparing machine learning algorithms including ANN, SVM, and DT. DT algorithm slightly outperformed the other data mining techniques followed by the SVM and ANN. In accordance with this report, our study revealed that although ANNs is satisfactory, DT and SVM offer a more desirable result for predicting the diagnosis of periodontal diseases. In respect of total computational time, DT algorithm was also slightly more successful than SVM with a performance of 7.00 s.

Unfortunately, there is still not any report comparing different diagnostic classifiers in the dental area, and there are limited studies about clinical decision support systems which are computerized information systems.[25] Speight *et al*.[11] evaluated individuals whether they have a prediction for developing oral cancer and precancer based on demographic and other risk factors with the use of a neural network. After the network gave a specificity of 77% and a sensitivity of 80%, the authors concluded that such a neural network may be valuable for identification of individuals with a high risk of oral cancer. Brickley and Shepherd developed a neural network and concluded that it is possible to train a neural network for lower third molar treatment planning decision.[12] ANNs have been trained in differentiation of subgroups of temporomandibular joint internal derangements (TMJ ID). The application of ANNs for diagnosis of subtypes of TMJ IDs was found to be useful supportive diagnostic method, especially for dental practitioners.[10] In a study of Xie *et al*.,[3] ANN was found to be effective in deciding whether extraction or nonextraction is necessary in malocclusion patients with 80% accuracy and ANN was reported to be an important decision-making tool within dentistry. In the presented study, ANN was not found to be successful for diagnosing periodontal diseases. This might depend on the limited performances of ANNs due to the uncertainty of selecting the number of neurons and layers. Although there are some empirical formulations for selecting those criteria, no exact formulation has been set up so far.

Support vector machine was previously used to diagnose dental deformities in cephalometry images and was found to be helpful in assisting dentists to quickly arrive at a conclusion whether a patient has been affected by any dental deformities or not.[13]

The presented study is the first to use algorithmic systems for diagnosing periodontal diseases and also it is the first to compare the results of three different algorithms in predicting the diagnosis.

The diagnosis of periodontal disease currently relies almost exclusively on clinical parameters and traditional dental radiography. However, the conditions may be aggravated by risk factors such as smoking, age, systemic factors, stress, gender, and educational levels.[26] One of the limitations of the presented study was the lacking part for systemic conditions as a risk factor, and the analysis was limited to clinical data in combination with some demographics. Certainly this limited the diagnostic sensitivity. The reason for this was the inadequate existing patient to classify such an input. Further studies may include all the accepted risk factors and immune-system involvements for periodontal diseases. There is a need for long-term studies including wider population, and more of the periodontal diseases should be added to the system for accurate diagnosis. This can be done by adding new material for decision-making algorithms. In our opinion, more accurate results can be obtained when larger number of patients with different types of periodontal and systemic problems continued to be added in the system and additionally a coding system for treatment planning may be developed for further studies. This kind of decision systems may also be useful for indicating risk factors for periodontal diseases and may be used for larger epidemiologic studies.

Based on our results, clinical decision support systems such as SVM, DT, or ANN derived from computerized machine learning techniques, made it possible for the clinician to predict the periodontal classification more objectively without biases and to determine the adequate therapy planning for periodontal diseases. The performances of the three algorithms could be ranked from the worst to the best as ANN − SVM = DT. ANN had the worst classification results in this study. That might be due to the nonlinearity relationship between input and output variables as well as selecting the number of layers arbitrarily. SVM and DT appeared to be sufficiently complex to reflect all the factors associated with the periodontal status, simple enough to be understandable and practical as a decision-making aid.

To sum up, DT and SVM offered a supportive diagnostic tool for periodontal diseases with high accuracy and opened a new area for identifying periodontal diseases. DT and SVM may be developed to assist especially dental practitioners in achieving correct interpretations and reducing human error. It may also be able to detect and distinguish patients carrying any risk factor for developing periodontitis. The system may also be developed to show the progression of the disease.

Conclusions

Decision-making algorithms are a new era in the field of dentistry, and there is a lacking part for periodontal diseases. Within the parameters of this study, diagnostic information was quantified and combined in an explicit way to serve as a tool for clinicians, not as a replacement for clinical judgment or experience. The codes used in the present study may be arranged globally, and more codings and conditions may be added to the algorithms to enlarge the scale and to catch any possibility. Therefore, a unique system for diagnosing periodontal diseases may be possible.

Further research with wider population is recommended, including research on advanced algorithmic models that use clinical and imaging data.

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