Original Article

Developing a Prediction Model for Periodontal Disease Using Ordinal Random Forest

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Abstract

Background: Periodontitis, a common inflammatory disease affecting oral health, is a major public health concern. Early detection of this disease is highly important in order to achieve less invasive and less costly treatment. The ordinal nature of different levels of periodontitis is usually not considered in many studies. It is often recognized and used as a nominal variable, in which case some information related to the ordinal nature is ignored. The aim of this study was to use continuation ratio logistic and ordinal random forest (RF) models to predict the three stages of periodontitis.

Methods: Overall, this study evaluated 300 patients referred to the Periodontology Department of Hamadan University, western Iran, between September 2016 and June 2018. The performance of continuous ratio logistic and ordinal forest models was evaluated using the same set of training and test data to predict different types of periodontitis (gingivitis, localized, and generalized periodontitis) based on input variables. Accuracy, kappa, gamma, Somers'd, and precision were utilized for comparison.

Results: The results confirmed the higher predictive ability of the ordinal RF model compared to the logistic continuation ratio model for all scoring indices (accuracy of 0.87 vs. 0.80). Alveolar bone loss, attachment loss, probing pocket depth, simplified oral hygiene index, and plaque index were identified as the most important variables.

Conclusion: Due to the ordinal nature of different levels of periodontal disease, the use of accurate prediction models such as ordinal RF is suggested since they can take into account the ordinal nature of the response in predicting and evaluating the effect of important variables. Ordinal RF is a well-suited machine learning technique for developing accurate predictive models of periodontal disease risk.

Keywords: Ordinal response, Classification, Periodontitis, Ordinal random forest, Continuation-ratio logistic model

Background

Periodontitis, a common inflammatory disease affecting oral health, is a major public health concern. Periodontal diseases are common and lead to physical, functional, and biological complications, as well as affecting the economic, social, and psychological dimensions of patients' lives. Periodontitis is a relatively silent disease that, if left untreated in its early stages, can lead to relatively irreversible damage to the supporting structures of the teeth, including the gingiva, periodontal ligament, and alveolar bone, and eventually to tooth loss (1-4).

The global prevalence of periodontitis is estimated to be 20%–50%. In Iran, the prevalence of periodontal disease has also been reported to be 20%–50%. The prevalence of gingivitis and periodontitis in patients between the ages of 35 and 70 years was 58.5% and 41.5%, respectively, in a study conducted in Rafsanjan, Iran (5).

Periodontitis is a chronic inflammatory disease of the gums that progresses through several stages. In the first stage, the plaque and gums are affected by an infection called gingivitis, which is an inflammation of the gums. The next stage involves the formation of plaque-filled

pockets, followed by further loss of the tooth's supporting tissues, leading to deeper pockets. Eventually, the tissue is destroyed, and the teeth may be lost. Symptoms of periodontal disease, such as bleeding gums, tooth shifting, and loss of the front tooth papilla, can affect a person's ability to eat, speak, socialize, and perform various daily activities (6-10).

The role of periodontal disease in several other serious health problems, such as cardiovascular disease, kidney disease, diabetes, endometriosis, and oral cancer, has also been reported. In recent years, more attention has been paid to the impact of periodontal disease on people's quality of life. Therefore, early detection of this disease is highly important to enable less invasive and cost-effective treatment (11-14).

Periodontal disease is a progressive condition that progresses through several stages, each characterized by increasing severity of symptoms and damage to the supporting structures of the teeth. Understanding these stages is essential for effective prevention and treatment. Early detection and treatment can effectively reverse gingivitis and manage more advanced stages of the disease (15).

As in all fields of medicine, successful treatment in dentistry is only possible with a correct diagnosis of the disease. A conventional diagnosis is made by a simultaneous clinical examination, X-ray, and objective evaluation of the patient's medical and dental history. The dentist uses the diagnosis as the basis for a treatment plan. Emphasis on staging and grading helps clarify the extent and complexity of the patient's periodontal condition, thereby influencing treatment decisions and prognostic expectations (16-18).

However, these examinations may not be sufficient, especially for inexperienced dentists, to make a correct diagnosis. Therefore, intelligent machine learning methods, such as artificial neural networks, support vector machines (SVMs), and random forests (RFs), can be applied in the development of decision support systems, as this capability has brought about a great change in healthcare. The development of such support systems can help dentists diagnose diseases and then organize effective treatment (16,17).

Predictive models have shown significant potential in the early detection of periodontal disease. There is a wide range of models for assessing the relationships between dependent and independent variables and predicting responses. Model selection is often achieved by measuring the scale of the response variable. In many medical and dental research studies, the response variable to be predicted or compared is ordinal in nature. Some examples are toxicity levels of substances rated as mild, moderate, or severe (18-20).

Although several studies have used machine learning techniques to build risk prediction models for periodontal disease, most of them have ignored the sequential nature of the different stages of periodontitis (16,21). Ordinal RF is an ensemble learning method that can effectively handle ordinal outcome variables, which is useful for modelling the progression of periodontal disease severity. It also provides insight into the relative importance of different risk factors (22).

Due to the ordinal nature of the different stages of periodontitis, this study aimed to use the continuation ratio logistic and ordinal RF models to predict the stages of periodontitis and then compare the performance of these models using the same training and test data sets.

Materials and Methods

The records of 300 patients (age range of the patients: 18-67 years) referred to the Periodontology Department of Hamadan University of Medical Sciences, Western Iran, between September 2016 and June 2018 were reviewed in this cross-sectional study. Variables were selected based on consultations with two experienced periodontists. The values of the desired variables for each patient were obtained from his file and recorded according to the principles of confidentiality. The periodontal examination of the patients included assessment of the periodontal condition and determination of pocket depth and plaque, assessment of clinical adhesion loss, and evaluation of the presence or absence of bleeding on probing.

Continuation Ratio Logistic Model

Assume that the response vector y_i belongs to one ordinal class k, where k = 1,..., K and i = 1,..., n (n: number of individuals). In addition, x_i represents a covariate vector of size p. A continuation ratio regression model, like binary logistic regression, models the logit rather than the probability modeling:

$$\log it\left(p\left(y = k|y \le k. \ X = x\right)\right) = \log\left(\frac{P\left(y = k|y \le k. \ X = x\right)}{P\left(y < k|y \le k. \ X = x\right)}\right) = a_K + \beta_K^T x$$

Therefore, the likelihood for the continuation ratio model is the product of the conditional independent binomial terms as follows:

$$L\left(\beta|y.k\right) = \prod_{i=1}^{n}\left(\prod_{j=2}^{K} \delta_j^{y_{ij}}\left(1 - \delta_j\right)^{1 - \sum_{k=j}^{K} y_{ijk}}\right)$$

$\beta = \left(a_2.\beta_{21}....\beta_{2p}....a_k.\beta_{k1}....\beta_{kp}\right)$ is a vector of parameter. A model including K − 1 different β vectors may be overparameterized. To simplify, one commonly fits a constrained continuation model, which includes the K−1 thresholds (α$_2$..... α$_K$) and one common set of p slope parameters slope parameters (β$_1$.....β$_p$). To fit a continuation ratio model, the original dataset can be restructured by forming K - 1 subsets, where for classes k = 2, ..., K, the subset contains those observations in the original dataset up to class k. In addition, for the k-th subset, the outcome is dichotomized as y = 1 if the ordinal class is k and y = 0 otherwise. Further, an indicator is constructed for each subset, representing subset membership. The K−1 subsets are then added together

to form the restructured dataset, which implies the K−1 conditionally independent datasets. Applying a logistic regression model to this restructured dataset yields a continuation ratio model (23,24).

The continuation ratio model is a type of ordinal logistic regression that focuses on the probability of being in a certain category or higher of an ordinal outcome.

Ordinal Forest Model

The ordinal forest model is an RF-based predictive classifier for ordinal response variables. RF, or random decision forest, is a supervised learning algorithm based on ensemble methods. In this algorithm, a collection of decision trees (DT) consisting of a group of trees is formed randomly. The method of forming a collection of trees is often called bagging. The main idea of bagging is that using a combination of learning models increases the overall accuracy of the model. Simply put, by randomly bagging multiple trees, decisions are made and combined to produce more accurate and stable predictions. The RF algorithm does not use all the sample observations to build the tree but selects a random sample by replacing the observations (bootstrap sampling). The selected observations are called experimental samples, and the remaining observations are called out-of-bag samples. DTs are constructed using learning observations, and out-of-bag samples are used to measure the impurity of the tree. The ordinal forest also calculates the variable importance measure, which describes which features are more relevant to the ordinal response (22,25-26).

Variables such as age, gender, smoking, attachment loss (AL), plaque index [PI (%)], probing pocket depth (PPD), gingival index (GI), alveolar bone loss (ABL; score: 0 for ABL < 20%, 1 for 20 < ABL < 50%, 2 for ABL > 50% based on radiographs), papillary bleeding index (PBI), mobility (MB), and simplified oral hygiene index were used as input (or independent) and different levels of severity of periodontal disease were considered as an ordinal output variable (or dependent) consisting of three classes (gingivitis, localized periodontitis, and generalized periodontitis).

From the information of 300 patients in this dataset, 200 people were randomly selected for the training dataset, and 100 people (including 55, 22, and 28 patients with gingivitis, localized periodontitis, and generalized periodontitis, respectively) were included in the test dataset.

To predict different levels of periodontitis based on the input variables, the performance of continuation ratio logistic and ordinal RF models was evaluated using the same set of training and test data. The models (continuation ratio logistic and ordinal RF) were trained and tested using 70% and 30% of the training and test data, respectively. The kappa statistic, gamma statistic, Somers'd, and accuracy were used for comparison. It should be noted that the gamma statistic and Somers'd are measures that take into account the ordinal nature of the predictions.

Results

The distribution of the study variables in the three stages of periodontitis is provided in Table 1. The values of several variables increase with an increase in the severity of the disease.

The percentage of smokers in generalized periodontitis was 18%, while that of smokers in localized periodontitis and gingivitis was 10% and 7.5%, respectively.

The results of using the continuation-ratio logistic model revealed that variables such as Al, PI, PD, ABL, and oral health have a significant effect on the occurrence of higher levels of periodontitis (localized and generalized) compared to gingivitis (Table 2). These findings are consistent with the results of identifying important variables based on the ordinal forest model. In the ordinal forest model, ABL, AL, PD, oral health, and PI were identified as the most important variables, respectively (Table 3 and Figure 1).

A coefficient of 0.96 was obtained for men (women in the reference category) in the continuation model. This coefficient shows that male patients are more likely to have higher levels of periodontitis (localized and generalized than gingivitis) compared to females with exp coefficient (0.96). Therefore, male patients are about 2.5 times more likely to be classified as having high-stage periodontitis.

The continuation ratio model gives a coefficient of 19.41 for oral health (0 as reference category: excellent, 3 as poor oral hygiene). This coefficient implies that patients with poor oral hygiene status are more likely to have higher levels of periodontitis (localized and generalized rather than gingivitis) compared to patients with higher levels of oral hygiene by a factor of exp (19.41). Thus, patients with poor oral hygiene status are more likely to be classified in the high stage of periodontitis.

The results of comparing the predictive performance of continuation-ratio logistic and ordinal forest models are presented in Table 4, confirming the higher predictive ability of the ordinal forest model compared to the continuation-ratio logistic model in all indices. The ordinal forest model could correctly predict the different stages of the disease in periodontitis patients with 87% accuracy.

Discussion

Accurate diagnosis of periodontitis plays an important role in determining treatment strategies that have a significant impact on the health of patients. Despite advances in treatment, no significant progress has been made in the diagnosis and prognosis of the disease, and diagnosis is usually highly dependent on empirical evidence. Therefore, this study sought to predict different levels of periodontitis and to identify the most important variables influencing it using logistic and ordinal forest models with a continuation ratio. The results of comparing the methods using the same test and training sets showed that the ordinal forest model had a better performance

Table 1. Comparison of the Distribution of Various Variables Between Three Classes (Stages) of Periodontal Disease

Variable		Gingivitis	Localized Periodontitis	Generalized Periodontitis
Age, Mean (SD)		32.91 (10.77)	33.88 (10.52)	34.23 (12.38)
Attachment loss, Mean (SD)		1.63 (0.47)	2.24 (0.61)	3.39 (0.81)
Plaque index (%), Mean (SD)		43.46 (17.82)	62.13 (17.80)	74.55 (15.09)
Probing pocket depth, Mean (SD)		1.48 (0.32)	2.01 (0.54)	3.25 (0.78)
Gender, No. (%)	Female	65 (40.6)	19 (31.7)	29 (36.3)
	Male	95 (59.4)	41 (68.3)	51 (63.8)
Smoking, No. (%)	No	148 (92.5)	54 (90)	65 (81.2)
	Yes	12 (7.5)	6 (10)	15 (18.8)
Gingival index, No. (%)	Grade I	48 (30)	6 (10)	5 (15)
	Grade II	78 (48.8)	24 (40)	27 (33.8)
	Grade III	31 (19.4)	26 (43.3)	39 (43.8)
	Grade IV	3 (1.9)	4 (6.7)	9 (7.6)
Alveolar bone loss, No. (%)	0	153 (95.6)	7 (11.7)	2 (2.5)
	1	4 (2.5)	18 (30.0)	32 (40.0)
	2	3 (1.9)	35 (58.3)	46 (57.5)
Papilla bleeding index, No. (%)	0	41 (25.6)	8 (13.3)	9 (11.3)
	1	78 (48.8)	22 (36.7)	13 (16.3)
	2	37 (23.1)	23 (38.3)	41 (33.7)
	3	4 (2.5)	7 (11.7)	17 (9.3)
Mobility, No. (%)	No	140 (87.5)	35 (58.3)	46 (57.5)
	Yes	20 (12.5)	25 (41.7)	34 (42.5)
Oral health, No. (%)	0	5 (3.1)	9 (15)	10 (12.5)
	1	16 (10.0)	16 (26.7)	11 (13.8)
	2	79 (49.4)	24 (40.0)	40 (50.0)
	3	60 (37.5)	11 (18.3)	19 (23.8)

(accuracy of 0.87%) for classifying periodontal disease.

Various studies have been performed to classify periodontitis using different approaches, most of which do not take into account the ordinal nature of the response in the prediction and scoring indicators. For example, Youssif et al (27) applied an artificial neural network model to classify periodontitis at three levels using 11 input variables. The accuracy of the model in correctly identifying different periodontal diseases based on 30 samples was reported to be 100%.

Ozden et al (21) developed prediction models (output variables at 6 levels using 10 input variables) using an SVM, DT, and artificial neural networks. The results of implementing these methods on 150 patients, including 100 patients in the training set and 50 patients in the test set, revealed that the DT and SVM models generally had better performance with an overall accuracy of 98%.

Farhadian et al (17) conducted a study to develop a decision support system based on SVMs for the diagnosis of various periodontal diseases. The data included information on 300 patients, output variables at three nominal levels, and 11 input variables. The SVM model based on the RBF kernel had the best performance in the test set with an overall accuracy of 88.7%.

According to the results of the ordinal forest model,

ABL was identified as the most important variable in the classification of periodontitis. Evidence confirmed that the extent of ABL can indicate the potential for tooth loss and the need for more aggressive treatment measures (28).

Probing PD plays a critical role in the classification and diagnosis of periodontal disease, according to the results of this study. The classification systems emphasize that probing depth is a critical indicator of periodontal health, with deeper pockets indicating more severe disease (29).

As poor oral hygiene is a major factor in the development and progression of periodontal disease, the results of the study confirm that oral health plays a significant role in the severity of periodontal disease. Therefore, maintaining good oral health is crucial in preventing and managing the severity of periodontal disease. Effective oral hygiene practices, regular dental visits, and awareness of the impact of the disease on overall health can significantly reduce the risks associated with periodontal disease (30).

Male gender is also associated with more severe periodontal disease than female gender. The preponderance of evidence suggests that male gender is an independent risk factor for more severe periodontal disease, probably due to a combination of poorer oral hygiene behaviors, differences in immune function, and

Table 2. Variable Coefficients Based on the Continuation-ratio Logistic Model

Variable	Coefficients	Standard Error	*P* Value
(Intercept)1	8.72	4.73	0.065
(Intercept)2	19.49	6.16	<0.001
Age	0.03	0.04	0.471
Attachment loss	-7.05	1.85	<0.001
Plaque index	-0.11	0.04	0.007
Probing pocket depth	-2.22	0.83	0.007
Gender			
Female (Reference)			
Male	0.96	1.15	0.400
Smoking			
Yes			
No	1.82	1.59	0.252
Gingival index			
Grade I (Reference)			
Grade II	1.99	1.42	0.162
Grade III	2.19	1.54	0.154
Grade IV	3.47	2.04	0.089
Alveolar bone loss			
0 (Reference)			
1	-8.12	2.17	<0.001
2	3.81-	2.00	0.057
Mobility			
Yes (Reference)			
No	1.79	1.14	0.116
Papilla bleeding index			
0 (Reference)			
1	2.63	1.37	0.054
2	0.59	1.41	0.674
3	1.96	2.20	0.371
Oral health			
0 (Reference)			
1	7.64	2.40	0.001
2	6.43	1.97	0.001
3	19.41	4.46	<0.001

Note. Reference category for ordinal response: Gingivitis.

Table 3. Coefficients of Important Variables Based on the Ordinal Forest Model

	Variable Important
Alveolar bone loss	0.2449
Attachment loss	0.0606
Probing pocket depth	0.0586
Oral health	0.0496
Plaque index	0.0396
Papilla bleeding index	0.0085
Gingival index	0.0048
Mobility	0.0042
Gender	0.0004
Smoking	0.0002
Age	0.0001

Table 4. Kappa, Gamma, Somers'd, and Accuracy Indices for Model Comparison

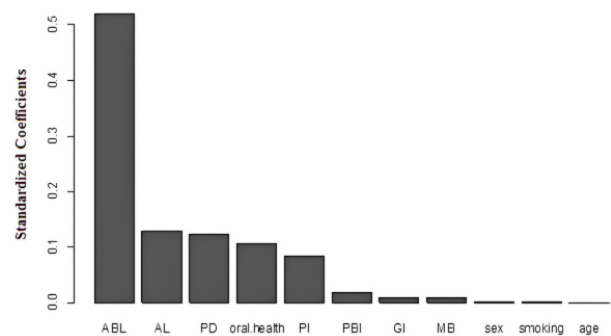|	Gamma	Somers'd	Kappa	Accuracy
Ordinal forest model	0.99	0.89	0.79	0.87
Continuation-ratio logistic model	0.95	0.83	0.67	0.80

Figure 1. Bar Plot of Important Variables for the Ordinal Forest Model

the distribution of data may be biased or unbalanced. These issues increase the risk of modelling bias and reduce model reliability, limiting the general use of predictive models.

Using an accurate model for predicting periodontitis, in addition to being highly predictive, maintains the ordinal nature of the response and can assist inexperienced dentists. In fact, using such systems can reduce fear (due to the lack of knowledge and skills, or loneliness) and increase self-confidence, especially in young doctors. These systems can be developed by designing and using decision-making systems in portable physician assistant devices or computers, and their development and evolution can lead to the satisfaction of the stakeholders of healthcare systems. Medical departments and offices provided real-time medical tools based on these prediction models to clinicians to make more reliable diagnoses.

Conclusion

Due to the ordinal nature of different levels of the periodontics disease, it is suggested that models be

other as yet unknown biological factors (31).

Although smoking was not identified as a significant variable, the results demonstrated that smoking is associated with increased severity of periodontitis. The association between smoking and disease severity may be due to the effect of smoking on the immune response and the promotion of the growth of pathogenic bacteria in the oral cavity (32).

Note, however, that the same test set was used to evaluate model predictive performance. In this regard, it is recommended that further studies evaluate the performance of the prediction model on the external dataset and determine its usability in clinical practice. In addition, because the prevalence of PD in clinical patient groups may differ from that in the national population,

used that can take into account the ordinal nature of the response in predicting and evaluating the effect of important variables. Ordinal RF is a well-suited machine learning technique for developing accurate predictive models of periodontal disease risk.

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Competing Interests
There is no conflict of interests.

Ethical Approval
This study was approved by the Research Ethics Committee of Hamadan University of Medical Sciences (IR.UMSHA. REC.1398.154).

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