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Neural Networks Based Prediction of Periodontal Disease Using Non-Intrusively Obtained Data

¹M.A. Faruqi, ¹S. Shah, ²R. Agarwala, ¹D. Sun and ¹J. Sai ¹Department of Civil Engineering, MSC 194,

Texas A and M University of Kingsville, Kingsville, 78363 TX, USA ²College of Technology and Computer Science, Suite 100 Science and Technology Building, NC 27858-4353, Greenville, USA

Abstract: Periodontal disease is a serious worldwide epidemic. It affects not only the dentition of the infected individual but also their overall health. Risk calculators for periodontal disease based on easily obtained data have been in use for years. However due to a number of factors that contribute to the disease, there has been no success in developing a model that provides a notable level of accuracy for predicting the disease patterns. In this study, we have developed neural network algorithms for predicting the presence and severity of periodontal disease in adults. The algorithm is based on dentists' evaluation and non-intrusively obtained data from patients' periodontal history. Results obtained from this basic study show that the approach can be used in predicting periodontal disease.

Key words: Neural networks, periodontal disease, non-intrusive, data, predicting, algorithms

INTRODUCTION

Periodontal diseases have plagued even the most developed nations for centuries (Rose et al., 2004). The disease causes tooth loss in affected individuals and numerous health challenges due to systemic exposure to gingival residing bacteria (Fedi et al., 2000). Risk factors have been studied for decades, resulting in a number of factors that cause increased risk of periodontal disease. Risk calculators based on statistical methods are also available but their usefulness is limited (Nield-Gehrig and Willmann, 2003; Lette et al., 1994). This is due to their inability to predict the presence and severity of periodontal disease. The interaction of risk factors is chaotic and there is little understanding of combined effects of the factors. The goal of this research is to develop a reliable method for periodontal prognosis of a patient using non-intrusively obtained data. This approach is a step towards a decision support system for dental hygienists for further evaluations.

MATERIALS AND METHODS

Data collection: Non-invasive data was obtained from patients using periodontal survey. The periodontal survey is shown after references. The survey was carried out during clinical portion of training of dental hygienists

at a dental hygiene college. A total of 150 patients were enrolled in the study. The data was used to train and test neural networks. About 11 patients with most common range of clinical dental disease were tested and evaluated with dentists' ratings. Details of chosen clinical variables in the survey and the dentists' evaluations are provided later.

Neural networks background: Neural Networks (NN) are massively parallel, distributed processing systems that can continuously improve their performance via dynamic learning. Correct application of neural or adaptive system can out perform other methods (Principe et al., 2000). NN are characterized by pattern and strength of connections between the various network layers, the number of neurons in each layer, the dynamic learning algorithm and the neuron activation functions. With supervised learning, the network is able to learn from the input and the error. Given the various available neural network architectures, 3 types were used in this study namely: multilayer perceptron; generalized feed forward and radial basis functions.

Multilayer Perceptrons (MLPs): MLPs are layered feed forward networks typically trained with back propagation. Their main advantage is that they are easy to use and can approximate any input/output map (Principe *et al.*, 2000).

Generalized Feed-forward Networks (GFN): Provide connections that can jump over one or more layers. In practice, generalized feed forward networks can solve the problem much more efficiently (Principe *et al.*, 2000).

Radial Basis Function (RBF): RBF networks are non-linear hybrid networks typically containing a single hidden layer of processing elements. This layer uses Gaussian transfer functions. These networks tend to learn much faster than GFN networks (Principe et al., 2000). Clinical variables used in the neural networks for predicting periodontal disease: Periodontal disease is loosely defined as any pathologic process that affects the periodontium (Fedi et al., 2000). For the purpose of this study, we define periodontal disease or perio as it will be referred to as any sub-gingival bacterial infection that would tend to result in inflammation, gingival recession, bone loss and finally tooth loss. Variables leading to perio for this study are provided. These are based on the general consensus of many dentists.

Input 1

pH: A pH paper was dipped into the patient's mouth, preferably near the sublingual gland. We made sure that the study was adequately moistened with enough saliva for an accurate reading. A higher salivary pH can correspond to a higher deposition rate. This contributes towards perio.

Input 2

Age: Age is an undisputed risk factor that contributes towards periodontal disease. Its contribution is significant due to other risk factors having adequate time to do their share of damage (Demetriou *et al.*, 1990). Perio is not restricted to the elderly but can also affect the young.

Input 3

Gender: There is no known advantage in being female. Some have suggested that women have better oral hygiene habits (Nield-Gehrig and Willmann, 2003).

Input 4

Race: The connection between race and perio is not very clear. Studies show that American-hispanic and African-American men have a higher incidence of perio than white men (Nield-Gehrig and Willmann, 2003). This may be more related to socio-economic level and oral health education since, there is no known physical or genetic difference between these races that would affect perio vulnerability.

Input 5

Oral home care: The development of perio requires the presence of bacteria in the form of plaque. Tooth brushing, flossing and anti-bacterial rinsing all contribute towards minimizing oral bacteria.

Input 6

Professional dental care: Most people will develop calcified plaque on their teeth. Plaque offers a porous surface for harboring bacteria (Fedi *et al.*, 2000). As plaque affixes to the gum line, it facilitates bacterial movement underneath the gums where it can damage the periodontal structure. Only a professional cleaning will remove the plaque.

Input 7

Genetics: There are known genetic conditions and markers that influence one's vulnerability to perio. Therefore, we obtained their parental dental data.

Input 8

Smoking: Smoking has long been accepted as a major risk factor for perio. Through systemic effects, it augments the progression of perio and reduces the effective eness of treatment.

Input 9

Medically compromised: This factor is particularly aimed at diabetes and autoimmune diseases. These diseases limit ones ability to resist bacteria. There is a well-known link between such diseases and perio (Fedi *et al.*, 2000).

Input 10

Iatrogenic factors: Iatrogenic factors spawn from previous dental work and include faulty crowns restorations and overhanging amalgams. These areas provide safe harbor for plaque, specially near the gum line. This speeds local infection and progression of perio.

Input 11

Anatomic factors: In this category, we included crowded and malpositioned teeth. The risk of this is the same as the iatrogenic factors. There are places that are difficult or impossible to clean.

Dentists' ratings: The dentists' ratings on a scale of 0-5 are provided for comparison with NN predictions:

- 0: Healthy
- 1: Gingivitis
- 2: Early periodontitis
- 3: Moderate periodontitis
- 4: Advanced periodontitis
- 5: Refractory periodontitis

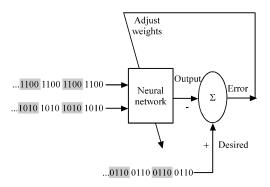


Fig. 1: Demonstration of neural network algorithm

Neural network algorithm and training: Perio results from a myriad of secondary causes and is therefore, a challenge to model. To attempt this, we entered the data obtained in a numerical format. Ideally, after training, the network was able to predict perio from new data with significant accuracy. The inputs were fed into the input layer and multiplied by interconnection weights as they were passed from the input layer to the hidden layer. Within the hidden layer, they were summed then processed by a nonlinear function.

As the processed data left the hidden layer, it again got multiplied by interconnection weights, then summed and processed. Finally, the data were multiplied by interconnection weights and processed one last time within the output layer to produce the neural network output. With each presentation, the output of the neural network was compared to the desired output and an error was computed.

This error was then fed back to the neural network and used to adjust the weights. This provided decreased error with each iteration and the neural model got closer to the desired output. This sequence of events was repeated until an acceptable error was reached or until the network no longer appeared to be learning. Figure 1 shows the neural network algorithm.

RESULTS AND DISCUSSION

The algorithm used the above mentioned NN models and the eleven inputs in periodontal prognosis. All 3 neural network models were run under varied training cycles and a number of hidden layers. Ultimately, MLP with 2 hidden layers and a training cycle of 20,000 epochs was chosen based on the quality of the output. Figure 2 shows neural network training and testing results. The results summarize the attributes of the network model used. It is observed that the Mean Square Error (MSE)

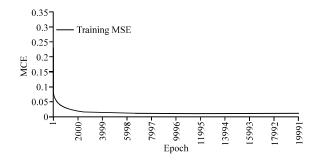


Fig. 2: Testing results; training: Minimum Mean Square Error (MSE) = 0.009949, Final Mean Square Error (MSE) = 0.010206; Testing: Nominal mean square error = 0.012473, Minimum absolute error = 0.013011, Maximum absolute error = 0.271682, Root mean square error = 0.994047

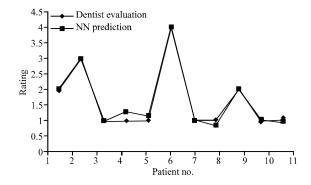


Fig. 3: Comparison of ratings

becomes constant after 12,000 training cycles. A final mean square error of 1% in training and a nominal mean square error of 1.2% in testing was observed. Figure 3 shows a comparison of dentists' evaluations and neural network prediction.

It is observed that the severity of disease is slightly overestimated (1.27 as compared to 1) and underestimated (0.85 as compared to 1), respectively in patient 4 and 8. This may be attributed to a smaller sample size.

CONCLUSION

In this study, we investigated the use of NN based prediction of periodontal disease using non-intrusively obtained data. It was found from this limited pilot study that the approach can successfully be used in predicting periodontal disease. This can further lead to advising patients regarding the severity of their disease.

APPENDIX

Clinician Unit #	Date:
Periodon	atal Survey
Please complete all information; partial forms will not be accepted. If the patient is unwilling to take part in the survey, please respect their wishes and do not continue or fill out a form. Please do not include the patient's name anywhere on the form. Please return all forms and attached samples to the folder labeled Periodontal Survey.	
Important: Please perform this section prior to pre-op rinse:	1-One parent 2-Both parents
1. Using the piece of pH paper included in the plastic bag, dip the paper in the patients' mouth, preferably near the sublingual gland. Make sure that the paper is adequately moistened with enough saliva for an accurate reading. Immediately return the paper to the plastic bag and seal it tightly. Take sample to clinic 1 instructor desk and use the pH indicator scale to determine the most accurate pH level.	C. Did either of your parents have significant natural tooth loss by age 60? 0-No 1-One parent 2-Both parents 8. Smoking:
Di	Does the patient smoke?
Please circle/fill out the best answer for each category.	0-No
2. Age:	1-Yes
3. Gender:	
0-Female	If yes:
1-Male	# of packs per week:
1 Maic	# of years patient has smoked:
4. Race:	9. Is the patient medically compromised?
1-White	(Diabetes, autoimmune disease, heart disease, etc.)
2-Hispanic	10. Iatrogenic factors:
3-African American	# of sites in mouth
4-Asian	(overhanging amalgam, faulty crown, etc.)
0-Other	
	11. Anatomic factors:
5. Oral hygiene:	# of sites in mouth
A. Tooth brushing frequency	(crowded or malpositioned teeth;
0-Occasionally	recession not related to perio.)
1-Once per day	
2-Twice or more per day	REFERENCES
B. Flossing frequency	Demetriou, N., A. Parashis and A. Tsami-Pandi., 1990.
0-Never	
1-Occasionally – less than once per week	Relationship between age and clinical symptoms of
2-At least once per week	periodontal disease. Stomatologia, 47: 231-241.
3-Two or three times per week	Fedi, P.F., A. Vernino and J. Gray, 2000. The Periodontic
4-Everyday	
C. Antibacterial rinse frequency (i.e., listerine, chlorhexidine gluconate; 0.12%)	Syllabus. 4th Edn., Lippincot Williams and Wilkin, Philadelphia, PA USA., pp. 258.
0-Never	Lette, J., B.W. Colletti, M. Usaf, M. Cerino and
1-Occasionally less than once per week	
2-At least once per week	D. Mcnamara et al., 1994. Artificial intelligence versus
3-Two to three times per week	logistic regression statistical modeling to predict
4-Everyday	cardiac complications after noncardiac surgery. Clin.
• •	
6. Frequency of professional:	Cardiol., 17: 609-614.
Dental care:	Nield-Gehrig, J.S. and D.E. Willmann, 2003. Foundations
0-<1 year	of Periodontics for the Dental Hygienist. Lippincot
1-Between 1-2 years	70 11
2-Between 3-5 years	Williams and Wilkin, Philadelphia, PA USA.
3->5 y ears	Principe, J.C., N.R. Euliano and W.C. Lefebvre, 2000.
7. Genetic influence:	Neural and Adaptive Systems: Fundamentals

7. Genetic influence:

0-No

2-Both parents

A. Did either of your parents have significant natural tooth loss by age 40?

B. Did either of your parents have significant natural tooth loss by age 50?

New York.

London, pp: 764.

Through Simulations. John Wiley and Sons Inc.,

Rose, L.F., B. Mealey and R. Genco, 2004. Periodontics: Medicine, Surgery and Implants. 1st Edn., Mosby,