APLICAÇÃO DE UMA REDE NEURAL ARTIFICIAL DE BASE RADIAL PARA SUPORTE AO DIAGNÓSTICO DE CÁRIES DENTÁRIAS ATRAVÉS DE RADIOGRAFIAS

APPLYING AN ARTIFICIAL RADIAL BASIS NETWORK FOR SUPPORTING RADIOGRAPHIC DIAGNOSIS OF DENTAL CARIES

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Resumo: Este estudo utiliza um modelo de inteligência artificial, uma rede neural com base radial (RBF), para dar suporte a diagnósticos radiográficos de cáries dentárias. Cento e sessenta imagens radiografias de faces proximais de dentes humanos extraídos foram avaliadas no que se refere à presença ou ausência de cárie por vinte e cinco examinadores. As condições reais de cada dente, denominadas gold standards, foram analisadas através de microscopia ótica. Estas gold standards foram empregadas para treinar a rede neural para diagnosticar cáries com base nos exames radiográficos. A fim de avaliar a capacidade da rede para a generalização, verificando o seu desempenho em relação a diagnóstico de novos casos, os dados foram divididos em dois subgrupos: subgrupo de treinamento e subgrupo de teste. Curvas ROC (Receiver Operating Characteristics) permitiram a avaliação da eficácia do diagnóstico com ou sem a utilização de redes neurais, mostrando que o modelo de inteligência artificial adotado melhorou significativamente o diagnóstico de cáries dentárias.

Palavras-chave: diagnóstico de cáries dentais, curvas ROC, redes neurais, inteligência artificial.

Abstract: This study uses an artificial intelligent model, a Radial Basis Function neural network (RBF), to support radiography diagnosis of dental caries. One hundred and sixty radiography images of proximal faces of extracted human teeth were analyzed by twenty-five examiners, which diagnosed the presence or absence of dental caries. The same teeth were then subjected to optical microscope analysis, which allowed the verification of their actual conditions. Such information was named as gold standards, and served to train a neural network to diagnose caries by means of radiography images. In order to verify the network's ability to diagnose new cases, data were organized in two subgroups: training subgroup and test subgroup. ROC (Receiver Operating Characteristics) curves allowed the comparison between diagnosis efficacy with or without the use of neural network, showing that the adopted artificial intelligent model significantly improved diagnosis qualities.

Keywords: dental caries diagnosis, ROC curves, neural network, artificial intelligence

1. INTRODUCTION

The prevalence of dental caries has experience a strong reduction over the last few decades, as well as alterations in the way as such disease is presented. Those changes are mainly due to the emphasis on the application of preventive measures, especially by the use of fluoride. As a consequence, dental caries are nowadays difficult to identify, which demands improvements of the diagnosis methods (Ie, Verdonschot, 1994), (Pine, ten Bosch, 1996), (ten Cate, 2001).

A number of diagnosis methods have been developed in order to support clinical exams. Conventional radiography or digital exams are the most frequently employed, and the contribution of bitewing radiography is widely recognized for caries diagnosis (Pine, ten Bosch, 1996). Among other methods mentioned in literature, we point out: laser fluorescence (Angmar-Mansson, 1993), fiber optic transillumination – FOTI (Mialhe, 2003), the electrical resistance test (Huysmans et al, 1995), ultrasound images (Angmar-Mansson, 1993), computerized tomography (Abreu et al, 2002) and magnetic micro-resonance (Lloyd et al, 2000).

All the previously mentioned studies compare two or more of the different methods for diagnosing caries and, as a result, each of them leads to better results for a specific region of the tooth. In most of the cases, the association of two or more methods is necessary (Lussi, 1993) for an appropriate analysis. The evaluation of a diagnosis technique may be assessed by means of ROC (Receiver Operating Characteristics) curves, which facilitate comparisons between different studies of various diagnosis methods. Fawcett (2004) presents an excellent overview concerning ROC curves theory and applications.

Over the last few decades, mainly due to computational resources, mathematical models have disseminated in the health area, in particular, methodologies based on artificial intelligence, consisting of non-invasive complementary support for diagnosis. Among these models, artificial neural networks play an important role, as stated by Brickley et al, 1998, Banis et al, 1994, Brickley, Shepherd, 1996 and Speight et al, 1995, were on can find some examples of neural networks as a support for medical diagnosis.

In the present study, a RBF neural network was trained to support radiography diagnosis of dental caries. Comparisons between the network and clinical analysis performed by examiners were made by means of the ROC curves.

2. METHODOLOGY

2.1. Odontology program

For the radiography evaluation of dental caries, phantoms constituted of human natural teeth distributed in order to simulate the posterior part of the dental arches were subjected to radiography analysis. An amount of 80 teeth presenting small proximal caries and no caries (sound teeth) were selected (40 premolar and 40 molar). The integrity of the occlusal face was also considered in the selection, and teeth with restorations or occlusal caries were excluded from the sample. The teeth were stored in a 0.1% timol solution after the extraction. Twenty canine teeth were employed in order to keep proximal contact. Each phantom was composed of five teeth: from canine to second molar. A total of 20 phantoms were obtained, from which ten simulated the superior arch e other ten simulated the inferior arch. The teeth were fixed with industrial silicone, with no overlapping of the proximal faces, which could affect the quality of the evaluation. The superior and inferior phantoms were articulated and fixed laterally to standardize the teeth position and to facilitate the obtaining of the bitewing radiographs. Two bitewing radiographs were taken from each set: one of the premolar region and another one of the molar region.

The radiographs were obtained with the help of a Heliodent 60B X-ray unit (Siemens, Brazil) with total equivalent filtration 2mm of aluminum (0.5mm of inherent filtration and aluminum filter of 1.5mm of thickness), operating 0.5s, 70kVp and 10mA. Insight periapical films were used (Kodak Eastman Co., USA). The focus-film distance was fixed in 40cm with the help of a standard device that provided a perpendicular incidence of the central beam of radiation. This device had a reservoir for a layer of 2cm of distilled water, placed between the X-ray source and objects, in order to simulate the attenuation of X-radiation for soft tissues. The films were processed manually by the temperature/time method (20oC/5min). The solutions were Kodak GBX (Kodak Eastman Co., USA). This work was approved by the ethical committee in research of the Piracicaba Dental School – UNICAMP.

The phantoms radiographs were mounted randomly in plates and evaluated by 25 examiners from different areas (radiology, operative dentistry, periodontology, pediatrics and general clinic). All of the examiners had at least 20 years of professional experience. Figure 1 illustrates a typical plate of bitewing radiographs used by the examiners for caries diagnose evaluations.

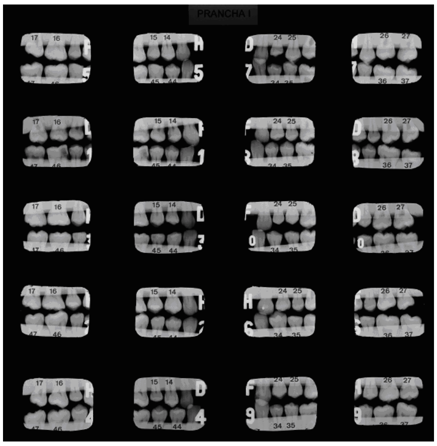

Figure 1: A typical plate of bitewing radiographs used to evaluation

The radiographs were evaluated individually in a view box, which allows the use of a 2x increase lens. The examiners received the necessary orientation and would have to evaluate the images of the proximal faces of all the premolar and molar teeth, by choosing one of the following scores: (1) definitively sound face, (2) probably sound face, (3) questionable face, (4) probably carious face, (5) definitively carious face. The results consisted of a total number of 160 examined faces.

After the radiography exam, the teeth were stored in methacrylate 5% and sectioned in longitudinal cuts whose thickness varied between 70 and 100µm in the proximal direction. These cuts were then subjected to microscopic analysis. The cuts were made with a hard tissue cutting apparatus (South Bay Technology, USA) fitted with a diamond disk, and under continuous cooling. Then the samples were mounted in slides using synthetic resin with xylol base (Entellan new) for observation under optical microscope (Jenamede-Carlzeiss, German) and examined at magnifications of 10 and 25 times by an experienced histologist. The actual teeth condition, named gold standard, was considered for the histological exam. Figure 2 illustrates typical grayscale microscopic images of two sectioned teeth (actual analyzed microscopic images were in color) and Table 1 presents a summary of gold standards for the analyzed surfaces.

The distribution of the examiners' answers is shown in Table 2. Note that the answers in Table 2 may be correct or incorrect, since the gold standard, obtained by the histological exam, is what really determines the presence or absence of caries. The results of microscopic assessment presented in Table 1 show that 74 proximal faces presented caries lesions and 86 were considered to be healthy.

Table 1: Summary of gold standards for the analyzed surfaces: Number of sound proximal surfaces, surfaces with enamel caries, caries in the enamel-dentine junction and dentinal caries.

	Number of surfaces
Sound	74
Enamel caries	45
Enamel-dentine junction caries	13
Dentinal caries	28
Total	160

Table 2: Examiners' answers distribution.

Scores	1	2	3	4	5	Total
Answers	2413	555	283	380	369	4000

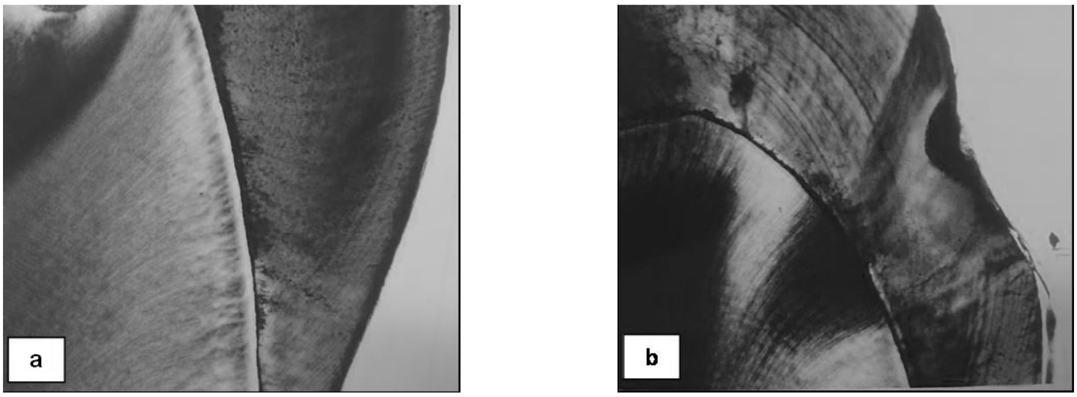

Figure 2: A typical microscopic evaluation of sectioned teeth (10x):
a) sound proximal surface; b) carious proximal surface.

2.2. The RBF neural network

From the set of 160 proximal faces, 49 (corresponding to 1225 of examiners' classifications) were randomly selected for training a neural network and 111 (corresponding to 2775 of examiners' classifications) were reserved for testing the trained network.

The basic form of RBF networks presents three layers: the input layer, one hidden layer that applies a nonlinear transformation in the input vector, and a linear output layer. These networks classify standards by transforming them to a high dimension space of non-linear form and then separating them into classes of linear form. The justification for this method is found in the Cover's Theorem about classification: when a non-linear transformation to a high dimension space is made, it increases the probability to make a linear separation.

The neural network employed in this experiment was a one non-linear hidden layer. The Figure 3 illustrates this neural network, where x_n (for n=1…25) is the nth input neuron, consisting of a set of 25 examiners' classifications from (1) to

(5) for an analyzed teeth face; f_n is the nth non-linear hidden layer neuron; and r is the output neuron, which contains the binary information: carious or not carious face teeth. In a RBF network, a neuron firstly calculates the distance, n, between input vector, x_n, and synaptic weights, w_n, and multiply n for the bias, b, then applies n on the radial function (Figure 4). These artificial neurons passed information from one layer to another, in a process that simulates a human synapse and the processed information produces an output signal (Brickley, Shepherd, 1997), (Brickley et al, 1997). The number of neurons at hidden layer was established by trial and error, using as criterion the network performance to provide correct diagnoses.

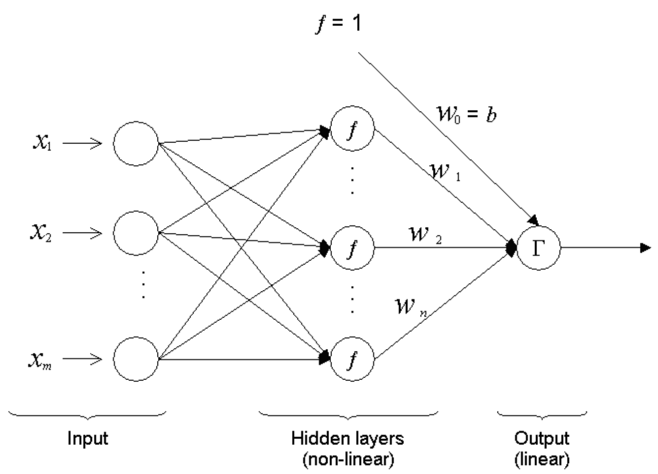

Figure 3: Architectural graph.

2.3. Diagnosis analysis based on ROC (receiver operating characteristics) curves

Caries diagnosis of the teeth faces may be classified into four categories, concerning their real conditions and the evaluated condition, as follows

a) “True Positives” : teeth faces are carious and were evaluated as carious;

b) “True Negatives”:teeth faces are not carious and were evaluated as not carious;

c) “False Negative”: teeth faces are carious and were evaluated as not carious;

d) “False Positive”: teeth faces are not carious and were evaluated as carious.

Based on these diagnosis classifications, it is possible to define “sensitivity” and “specificity” as follows:

$$sensitivity = \frac{TP}{P}$$

$$specifity = 1 - \frac{FP}{N}$$

where: TP is the total of true positives classification diagnosis; P the total of actual positives diagnosis; FP the total of false positives classification diagnosis; and N the total of actual negative diagnosis. In that way, for a set of diagnosis classifications, it is possible to achieve an ordinate pair (1-specificity; sensitivity), resulting in a graphical representation which is the basis of ROC curves. Figure 5 illustrates four sets of diagnosis classifications (A, B, C and D points).

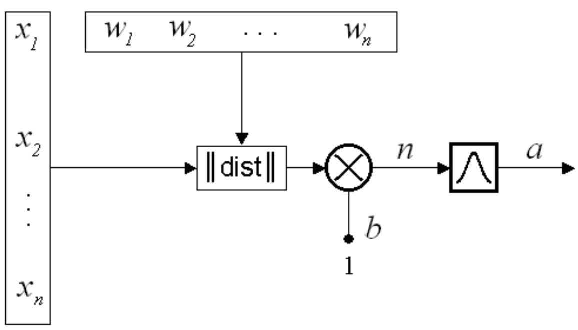

Figure 4: An RBF artificial neuron.

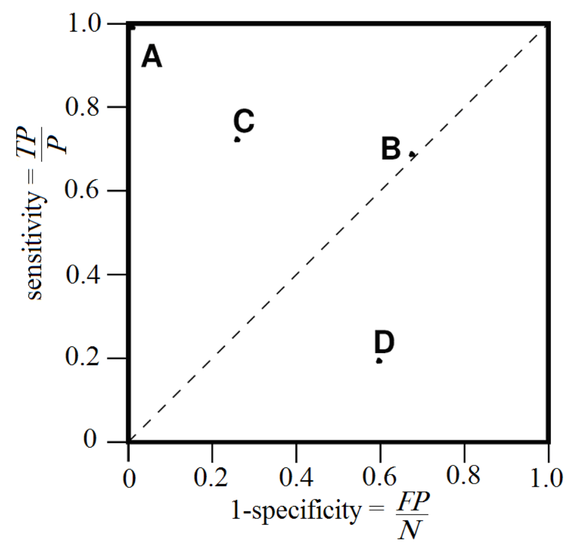

Figure 5: A graphic showing four ordinate pairs attached to four sets of diagnosis classifications.

In the Figure 5, Point “A” represents the perfect diagnosis classification: 100% of probability of TP and 0% of FP. On the other side, “B” point or any point placed on the diagonal line indicates a random performance in the classification (50% of TP and 50% of FP). Points “C” and “D” indicate that the diagnosis was supported by some information attached to the dentist competence, although in “C” point, this information was correctly used.

In general, a neural network used to support diagnosis produces a binary output. In the present work this output is carious or not carious face teeth and this decision is made by analyzing an output probability. If a threshold varying from 0 to 1 is defined in order to produce the binary classification, for each threshold level one has a point in the ROC curve. The same idea may be applied for the discrete diagnosis classifications of each dentist. In these cases, instead of a probability, the output classification is a score from 1 to 5 and it is possible to define threshold levels varying from 1 to 5.

Figure 6 shows the ROC curve obtained for the best examiner. ROC curve areas vary from 0 to 1 and they are frequently used in order to compare quality of diagnosis. The perfect diagnosis classification leads to a ROC curve area of 1 (one) and a completely wrong diagnosis classification has ROC curve area of 0 (zero).

A neural network ROC curve was constructed for the classifications relative to the set of the 4000 classifications and it is presented in Figure 7, having an area of 0.8702.

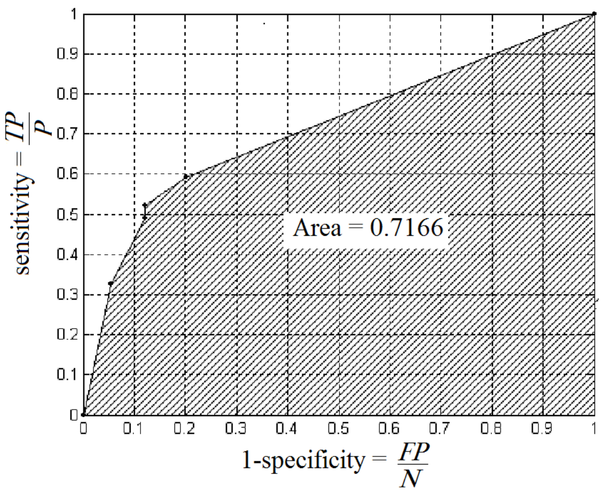

Figure 6: The ROC curve obtained for the best examiner.

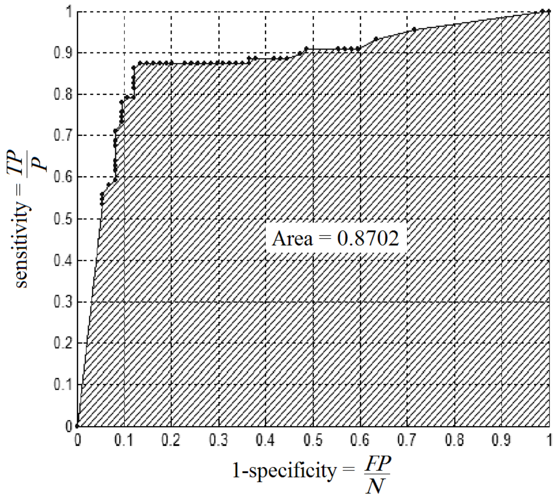

Figure 7: RBF network ROC curve.

A set of 25 ROC curves (one ROC curve for each examiner) were carried out and their areas are presented in Figure 8, which also shows a reference horizontal line with the RBF ROC curve area. The mean of examiners' ROC curve areas was 0.6323, with a standard deviation of 0.045.

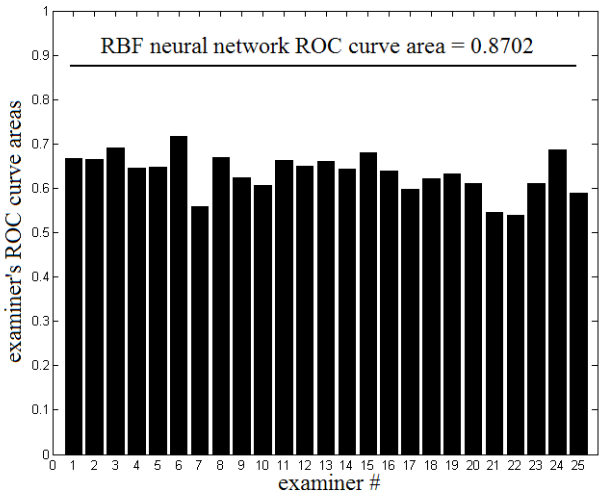

Figure 8: ROC curve areas for the 25 examiners in the vertical values and labels from 1 to 25 for each examiner in the horizontal axes. The horizontal line in this figure represents ROC curve area for the RBF network.

3. RESULTS AND DISCUSSIONS

According to the difficulty in identifying alterations due to caries lesions, the application of more precise diagnosis methods is really advisable, both in the clinical and epidemiological spheres.

The interpretation of the results of the different diagnostic tests, as well as the treatment given to these results should also be optimized as an attempt to reduce the rate of false-positive and false-negative results, which lead to diagnostic errors and, consequently, wrong decisions about treatment. In the case of dental caries, a false-negative result leads to non-treatment of caries lesions, which are existent but not detected, while the false-positive answers are considered even more harmful, because result in unnecessary interventions in healthy teeth.

In the present work, the mean area under the ROC curve resulted in 0.6323 for the classifications without the use of the network and in 0.8702 for the classifications supported by the neural network, which provides a difference of 0.2379 percent points. It means that the amount of correct diagnosis increased of 37.62% when aided by the neural network. Even when considering the best examiner, the performance of the neural network is still considerably superior (18%). These numbers correspond to a significant improvement in diagnostic ability when the neural network is used. Comparisons with other similar studies in literature are difficult to make, mainly because this is a quite recent methodology. At the moment, the use of neural networks is rather limited to the medical area, and very few studies have been developed in the dentistry sphere. In particular, up to this moment, no study was found in the literature concerning the clinical diagnosis of dental caries modeled by this method of forecasting events.

Brickley et al (1997) makes a detailed review about neural networks, emphasizing its possible applications in Dentistry, as an aid to interpreting radiographies, in the assessment of cytological rubbings, for use in anesthesia monitoring systems among other innumerable possibilities. Brickley and Shepherd (1997) affirm that in addition to its importance to clinical dentistry, this system of computer aided decision making would also be of great use in the longitudinal monitoring of patients in a community and as aid in training Dentistry students. Some areas of Dentistry in which artificial intelligence system has already been used include the following: the area of diagnosis, with the application of the neural network to identify persons at high risk of oral cancer (Banis et al, 1994), in surgery, aiding in decision making about the treatment of third molars (Brickley, Shepherd, 1997), (Speight et al, 1995), (Brickley, Shepherd, 1996) and in periodontics (Brickley et al, 1998).

In the present study, it was identified another potential application of the neural network in Dentistry, and one concludes that the use of a suitable neural network may significantly improve the performance of diagnosing dental caries. It is important to notice that no mathematical model used up to now in the sense of optimizing dental caries diagnosis has shown itself to be sufficiently precise or complete, due to the biological complexity of this disease.

Clinical application of the presented work may be implemented using an Internet web server. To this end, the group of twenty-five examiners has only to make similar classifications (from 1 to 5) concerning radiographies posted in the internet and after all twenty-five classifications, the already trained neural network is able give a diagnosis.

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