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Dariusz Świetlik[1]
Cezary Kłosiński[2]

[1]Laboratory of Medical Informatics and Neural Networks,
Medical University, Gdańsk, Poland
[2]Department of Prosthodontic Dentistry,
Medical University, Gdańsk, Poland

# USING ARTIFICIAL NEURAL NETWORKS TO PREDICT FOLLOW-UP VISITS (NUMBER OF CORRECTIONS)

## SUMMARY

**The aim of the study was to demonstrate the usefulness of artificial neural networks for predicting the number of follow-up visits (number of corrections). We used clinical data of 82 patients 48-90 years of age, mean age 66 ±9 years (38 males and 44 females) for whom a total of 164 complete dentures was performed (82 upper complete dentures and 82 lower complete dentures). The actual number of corrections was compared with the number obtained using a neural network. Pearson's linear correlation coefficient (r) was 0.86 ($p <$ 0.05) and the coefficient of determination was 0.74. Artificial neural networks are a useful tool which employs artificial intelligence techniques for the prediction of the number of follow-up visits.**

***Key words:*** **artificial neural networks, complete denture, prosthetic treatment, edentulous jaws, adaptation**

## INTRODUCTION

Loss of teeth leading to toothlessness is regarded by all the affected patients as some sort of disability. Efficient function of the entire stomatognathic system requires the presence of the patient's own teeth. Toothlessness impairs mastication and speech, and affects the patient's appearance. Complete dentures placed in the patient's oral cavity are intended to restore the lost masticatory function and improve the patient's pronunciation and appearance. The full success of treatment with complete dentures not only depends on the team composed of the dentist and dental technician but also on appropriate dentist-patient co-operation. The final success of treatment is not only dependent on the correct clinical and laboratory procedures but also, to a large extent, on biological and psychological patient's factors.

Non-physiological transmission of masticatory forces (mucous membrane – submucous membrane – periosteum – alveolar bone) by complete dentures results in reduced function and masticatory force and consequent alveolar resorption. The lack of periodontal proprioreceptor activity makes it impossible for the bone to be stimulated for restorative remodelling. Alveolar bone resorption is an unavoidable process which follows tooth extraction, which progresses with age and as a result of changes in the transmission of bone load (1). The conditions of the basal seat that worsen with age (depending on such factors as the patient's health, calcium and phosphorus metabolism, nutritional status) also affect the rate of adaptation to new complete dentures. Speech articulation may also be affected due to the restricted tongue space. The taste and temperature sensation are also impaired. There are also restrictions with respect to certain foods (glutinous and hard foods should be avoided). Mastication of food must be evenly distributed on both sides of the dental arches. Biting hard chunks of

Corresponding author • E-mail: dswietlik@amg.gda.pl

food off with anterior teeth may lead to the loss of denture retention. When the teeth (whose function as receptors) are lost, the reflex arch between the teeth, the periodontium and the masseter muscle are broken. The muscle tone increases and the mandible is lifted. The normal abduction and adduction of the mandible are impaired leading to its abnormal function and shape(1).

When the new complete dentures are adjusted and given out to the patient, an adaptation period begins, which is affected by the complexity of morphological and functional changes in the stomatognathic system as well as the psychological factors. According to Mäkilä, the rate of adaptation is dependent on the patient's anatomy(2).

The most common methods of artificial intelligence used in dentistry are artificial neural networks (3-7). Artifical neural networks have been used to diagnose lip cancer (3), to make pretherapy decisions in patients with head and neck cancer (4) and to make surgical decisions in the case of the third molar (5, 6).

## MATERIAL AND METHODS

We analysed data from clinical charts of 82 patients 18-90 years of age (mean age: 66 ± 9 years, 38 males and 44 females) for whom a total of 164 complete dentures was performed (82 upper complete dentures and 82 lower complete dentures). The information from the patient charts concerned the number of follow-up visits (number of corrections) and factors which might determine the adaptation to newly performed complete dentures, such as age, duration of removable prosthetic restorations use, sex, Supple class, previous partial removable prosthetic restorations, previous complete removable prosthetic restorations, general health, course of adaptation to the previous dentures, shape of the edentulous alveolar arches of the maxilla and the shape of the edentulous alveolar arches of the mandible.

The study included patients managed at the Department of Dental Prosthetics, Medical University of Gdansk, between 2003 and 2004.

## ARTIFICIAL NEURAL NETWORK

An artifical neural network is a set of technical elements or an algorithm whose action reflects the functioning of a nerve cell (8). A technical device realising a neural network is built of electromechanical and/or electronic systems. An algorithm is written in one of the programme languages realising the neural network as a computer programme simulating the work of such a device. A contemporary software simulator of artificial neural networks is an advanced computer programme which provides the user with such options as the selection of architecture, learning algorithm and other parameters.

An artificial neural network is made up of interconnected single elements, the so-called neurons, which make up subsequent layers. Individual neurons have a prespecified number of inputs and outputs. The outputs of the individual layers are connected with the inputs of others on an "all-to-all" basis except that the elements from one layer do not share connections *(Figure 1)*.

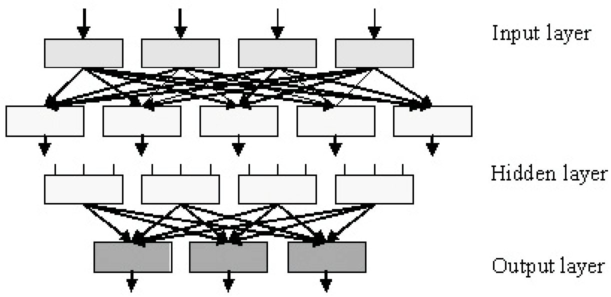


*Figure 1. A feedforward artificial neural network*

For each neuron, the relations between the inputs and outputs are modified during the learning process. The learning process of an artificial neural network is realised in the form of available mathematical algorithms (e.g. error back-propagation, BP). In the simplest form, during the learning process, the user presents the artificial neural network with examples along with the expected answer. Following an automatic learning process the neural network is tested for new, unknown data which have not been presented previously.

### Input data for the artificial neural network

A set of 10 variables was obtained for each patient. These variables were the input signals for the neural network. Detailed characteristics of the variables are presented in *Table 1*.

### The architecture of the artifical neural network

We used a multilayer perceptron network in our study *(Figure 2)*.

The artificial neural network consisted of three layers: the input, hidden and output layers of 10, 4 and 1 neurons, respectively. Using a software simulator of artificial neural networks, we created networks which solved regression task which consisted in pre-

*Table 1. Input signals for artificial neural network*

| Variable | Unit |
|---|---|
| Age | years |
| Duration of removable prosthetic restorations use | years |
| Sex | M, F |
| Supple class | I, II, III, IV |
| Previous partial removable prosthetic restorations | YES, NO |
| Previous complete removable prosthetic restorations | YES, NO |
| Was the general health satisfactory? | YES, NO |
| What was the course of adaptation to the previous dentures? | very good, good, poor |
| Shape of the edentulous alveolar arches of the maxilla | triangular, square, oval, irregularly oval, bulb-like |
| Shape of the edentulous alveolar arches of the mandible | triangular, square, oval, irregularly oval, bulb-like, atrophic |

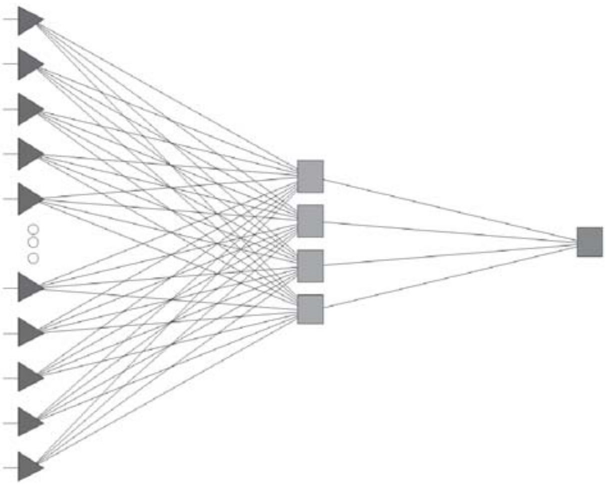

*Figure 2. Artificial neural network*

dicting the number of corrections. The answer of the artificial neural network to each test case fell within a numerical range of 0 to 4. The activation and rejection levels for the output neuron were selected automatically by the stimulator of artifical neural networks in order to minimize the losses. During the learning process, the weight links between the neurons were modified using the error back-propagation algorithm. The sum of squares was selected as the error function. The artifical neural network error is the sum of squared differences between the given values and the values obtained at the output of the output neuron. A sigmoid (logistic function) was used as the activation function. The learning coefficient was 0.01 and the inertia was 0.3. The value of 300 epochs was established, where the order of presented cases for the neural network was different in each epoch. The initialization of neural network weights was conducted by random Gaussian method.

One of the sampling method was used for the evaluation of the diagnostic quality of artificial neural networks, namely the cross-test of the leave-one-out type. Of the 82 patients, one case was left out for testing and the remaining 81 were used for teaching the neural network. The process was then repeated 82 times so that each case could be placed in the test set. The number of times the artificial neural network was taught reflected the number of cases (82 times), leaving out a different case for teaching each time. The results obtained for the 82 test cases were pooled to calculate the diagnostic quality of the artificial neural network.

## RESULTS

The number of corrections obtained from the artificial neural network was compared with the actual number of corrections performed by the dentist and was presented in a graph (Figure 3). Pearson's linear correlation coefficient r was 0.86 ($p < 0.05$). The regression equation was as follows: $y = 0.28953 + 0.80555\ x$.

The correlation coefficient expresses the linear relationship between the number of corrections actually performed and the number of corrections obtained from the artificial neural network. When the correlation coefficient is squared, a coefficient of determination is obtained, which is equal to 0.74. It expresses the power of association between the actual number of corrections and those obtained from the neural network.

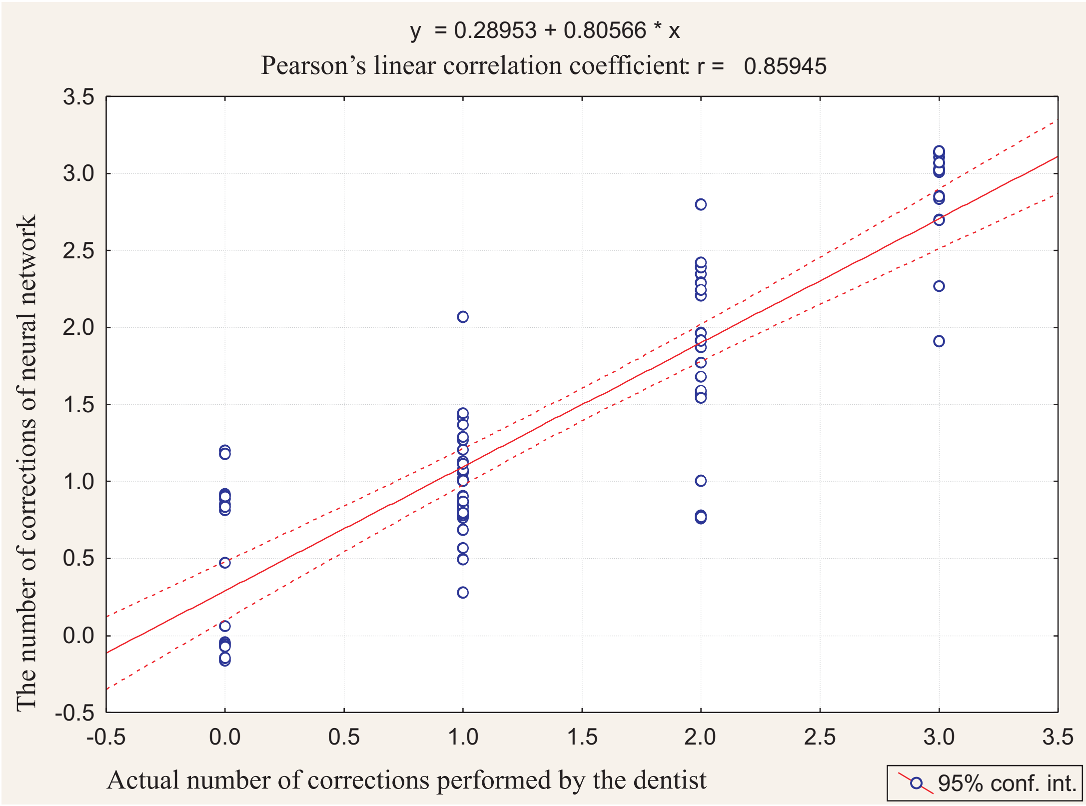


*Figure 3. Actual number of corrections performed by the dentist and the number of corrections obtained from the artificial neural network*

DISCUSSION

Our study yielded a high Pearson's linear correlation coefficient in predicting the number of corrections using an artificial neural network versus the actual number of follow-up visits. Brickley et al. used artificial neural networks in planning the third molar surgical decisions. They used the clinical history of 174 patients. For the artificial neural network they obtained a decision sensitivity of 78% and a surgeon sensitivity of 88% with the respective specificities amounting to 98% and 99% (5).

Speigh et al. employed artificial neural networks to identify the patients at risk of lip cancer. Their artificial neural network used a population of 1662 patients in the learning process and 365 cases in the testing process. The sensitivities were 80% and 74% for the neural network and the doctor, respectively, and the specificities were 77% and 99% for the neural network and the doctor, respectively (3).

Goodey et al. employed an artificial neural network to predict the surgical decision in patients with the third molar (6). Their study compared the sensitivity of this decision for the neural network with the dentists' opinion and with the clinical algorithm which utilized the NIH criteria (9). The sensitivities obtained for the neural network, the dentist and the clinical algorithm were 56%, 97% and 56%, respectively, while the respective specificities amounted to 79%, 22% and 93% (6).

In the cited bibliography, the authors who compared the sensitivities of neural networks with those of dentists obtained similar results (3-5). In one study, however, the sensitivity of the third molar surgical decision obtained using the neural network was lower than the one obtained by the dentist (6). The same study, however, reports a higher specificity of the neural network than the one obtained by the dentist. The neural network was more effective in excluding a surgical decision where one should not be used.

Our work demonstrates that artificial neural networks are a useful tool which employs artificial intelligence techniques in predicting the number of follow-up visits (number of corrections). They help dentists in their everyday practice.

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## PRIMENA VEŠTAČKIH NEURALNIH MREŽA U PREDVIĐANJU BROJA PREGLEDA (BROJA KOREKCIJA)

Dariusz Świetlik[1], Cezary Kłosiński[2]

[1]Laboratorija za medicinsku informatiku i neuralne mreže,
Medicinski fakultet, Gdanjsk, Poljska
[2]Odeljenje za prostodonciju, Medicinski fakultet, Gdanjsk, Poljska

### SAŽETAK

**Cilj studije bio je da se prikaže korisnost primene veštačkih neuralnih mreža u predviđanju broja pregleda (broja korekcija). Koristili smo podatke dobijene od 82 bolesnika starosti 48-90 godina, prosek 66±9 godina (38 muškaraca i 44 žene) kod kojih su ugrađene 164 kompletne proteze (82 gornje kompletne proteze i 82 donje kompletne proteze). Pravi broj korekcija je upoređen sa brojem dobijenim primenom neuralnih mreža. Parsonov linearni koeficijent korelacije bio je 0.74. Veštačke neuralne mreže su korisno sredstvo koje primenjuje tehnike veštačke inteligencije za predviđanje broja pregleda.**

***Ključne reči:*** **veštačke neuralne mreže, kompletne proteze, protetski tretman, edentulozne vilice, adaptacija**