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RESEARCH ARTICLE

Backpropagation Multilayer Feedforward Neural Network for deciding treatment for broken Tooth

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Abstract

People around the world are suffering from the problem of broken tooth over years. Dentists are uncertain in deciding the treatment plan for chip off tooth. In this study, Backpropagation Multilayer Feedforward Neural Network (BPNN) based decision making tool is proposed to recognize a treatment plan(s) for fractured tooth. The system has been designed to simulate the conduct of a dentist while choosing an appropriate treatment plan for the fractured tooth. To design the system, a dataset involving of 60 records has been assembled. The accuracy of the proposed system enhances the confidence level of dentists while making decision for treatment plan(s).

Keywords: Artificial neural network, learning, sign-symptoms, BPNN, dental treatments, fractured tooth, MATLAB.

Introduction

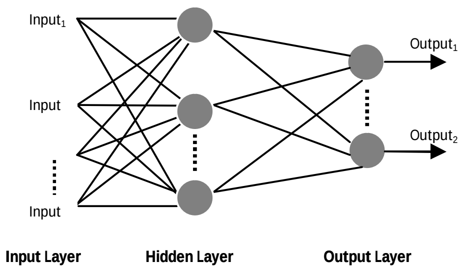
Knowledge-based analysis is becoming foreseeable in disease diagnosis, especially when the conventional manual data analysis techniques are not effective in diagnosis. Due to the fact that medical domain has become too complex and uncertain to decide a treatment plan for a medical problem, therefore it is time to develop effective and efficient computer-based systems for decision support. These systems would not only assist physician in deciding the treatment plan(s) but also make the life of patient more secure and happy. There are numerous soft computing techniques for supporting the decision in clinical diagnosis systems, which includes Fuzzy Logic (FL), Artificial Neural Networks (ANN), Bayesion Networks (BN). But ANN is one of the prominent methodologies for recognizing and classification of the pattern, especially during diagnosis of a medical problem. Problem of fractured tooth is very common among all people, specifically in young and old ones. Teeth usually break as a result of trauma from biting down on something hard or accidentally. The other reason of chipping or fracture is weakening of the tooth due to dental cavities. If a large piece of the tooth breaks off, it can hurt because the nerve inside the tooth may be damaged. When a tooth cracks or fractures it may or may not hurt. Minor tooth fractures are unlikely to cause symptoms. Deeper fractures can be painful because the damage may extend to the nerve inside the tooth. Pain from fractures may be constant or may come and go. Many people feel pain when they chew because as they chew they apply pressure to the tooth. As the fractured tooth bites down on the food, the crack in the tooth gets wider, but once the pressure is released, the crack closes again. Larger fractures may cause a portion of the tooth to break off (Walmley *et al.,* 2002).

ANN-based methodologies have been developed and broadly practice in medicine. A three-layered BPNN was developed to classify the seizure episodes in rats by Sinha (2002). The results produced by proposed BPNN were having a high recognition rate of 98.6%. While in the study by Guler and Ubeyl (2003), a least-mean square BPNN was used to detect the presence or absence of ophthalmic artery stenosis. Ophthalmic artery Doppler signals were successfully classified with the accuracy of 88.9 to 90.6%. Shanxiao and Guangying (2010) proposed a system classification of Electrocardiogram (ECG) arrhythmias. The system includes two phase: extraction and classification. In extraction phase, DWT is used for extracting feature values of each arrhythmia. In classification phase, obtained features from first phase are used as an input to BPNN for classification of ECG arrhythmias.

ANN was developed for predication of Thrombo-embolic stroke by Shanthi *et al.* (2010). Using this system, physicians can plan better medication. The success rate of proposed system was 89%. Qeethara (2011) proposed feed-forward back propagation network that correctly diagnosis heart disease to 99%; the percent correctly classified in the simulation sample by the feed-forward back propagation network is 95%. The BPNN classify exudates and non-exudates at accuracy of 98.45% (Asha *et al.,* 2011). Arti and Maneesh (2011) proposed a classifier based on BPNN to distinguish between infected and non-infected person. The result of the diagnosis is better than diagnosis done by physician (Sumathi and Santhakumaran, 2011). The system effectively predicts and diagnosis the patients with hypertension.

Comparison between Backpropagation and Naive Bayes classifier is done to diagnose hepatitis disease (mathworks.com). The overall accuracy of systems was 98 and 97% respectively. In this study, a novel approach is proposed for medical decision making, which aims to assist dentist to regulate an appropriate treatment plan to be used for fractured tooth. In this approach, Graphical User Interface (GUI) based BPNN classifier is used to predict the magnitude of ailing tooth and determine suitable treatment plan. The data in form of sign-symptoms are fed to the system and the result is instantaneously accessible to the dentist for further handling.

Fig. 1. A Backpropagation Feedforward Neural Network.



A BPNN is a fully connected, layered, feed-forward neural network and is shown in Fig. 1. The flow of data is unidirectional: from input layer to output layer through hidden layer. Every neuron in a layer is connected to each neuron of next layer in forward direction. BPN may contain multiple hidden layers. Knowledge of the network is encoded in the weights between neurons. The activation levels of the output layer neurons determine the output of the whole network. BPN commences with a random set of connection weights. The network regulates its weights according to some learning rules each time it observes a pair of input-output vector. Every pair of vectors goes through two phases of activation: a forward pass and a backward pass. The forward pass implicates producing the network a sample input to the network and allowing activation flow until they reach the output layer. During the backward pass, the network's actual output is compared with the target output and errors are compared for the output layer neurons. The weights connected to the output neurons can be adjusted in order to reduce those errors. The error estimates of the output layer neurons are then used to obtain error estimates for the neurons in the hidden layer. After all, errors are back propagated to connections stemming from the input layer neurons. Later than each solution of forward-backward passes, the network learns incrementally from input-output pair and reduces the error between the network's proposed output and the actual output. Although one can adjust a neural network to lower its errors but can never be sure of lowering of the error. This is can be done through the concept error surface (the error plotted as function of the configuration of weights).

The aim of network training is to find the lowest point in this many-dimensional surface. Since NN error surfaces are very complex, it is impossible to analytically determine where the global minimum of error surface is, so NN training is essentially an exploration of the error surface. Typically, the slope of the error surface is calculated at the current point, and used to make a downhill move. Finally, the algorithm stops in a low point, which may be a local minimum. In back-propagation, the gradient vector of the error surface is calculated. This vector points along the line of steepest descent from the current point, so one know that if one moves along it a short distance, one will decrease the error. The difficult part is to decide how large should be the step size. In practice, the step size is proportional to the slope and to the special constant: *learning rate*.

The algorithm therefore progresses iteratively, through a number of epochs. On each epoch (an epoch corresponds to a given number of training cycles), the training cases are each submitted in turn to the network and target and actual outputs compared and the error calculated. This error, together with the error surface gradient, is used to adjust the weights, and then the process repeats. The initial network configuration is random and training stops when a given number of epochs pass by, or when the error reaches an acceptable level, or when the error stops improving.

Materials and methods

Experimental design: In this study, we assume that the age, tooth structure, mobility and pain are four different parameters to be used as the input to the designed system. The treatment process will be determined according to the parameters and their respective values. There are seven treatment policies which can be used for the affected tooth. These include medication, bite relieve, splinting, remove sharp edges, filling, root canal treatment and extraction. The input layer of the system proposed consists of four input neurons. All four sign-symptoms; type of tooth (age), tooth structure loss, mobility and pain are input neurons. The hidden layer consists of 15 neurons for effectively convergence of the network. The weights on the synapses input layer-hidden layer are automatically adjusted by the system during convergence. The output layer of the network contains the seven different treatment plans for fractured tooth.

Calculation of the actual output is done using the following equations:

$$y_1, y_2, \ldots y_n$$

$$i = 1, 2, \ldots . \mathrm{n}$$

$$y_i = \Phi\left(\sum_{j=1}^{n} w_{ij}{}^{(M-1)} x_j{}^{(M-1)} + b_j{}^{(M-1)}\right)$$

Adaption of weight (w_{ij}) and bias (b_i):

$$\Delta w_{ij}^{(i-1)}(n) = \mu x_j(n)\delta_i^{(i-1)}(n)$$

$$\Delta b_i^{(i-1)}(n) = \mu\delta_i^{(i-1)}(n)$$

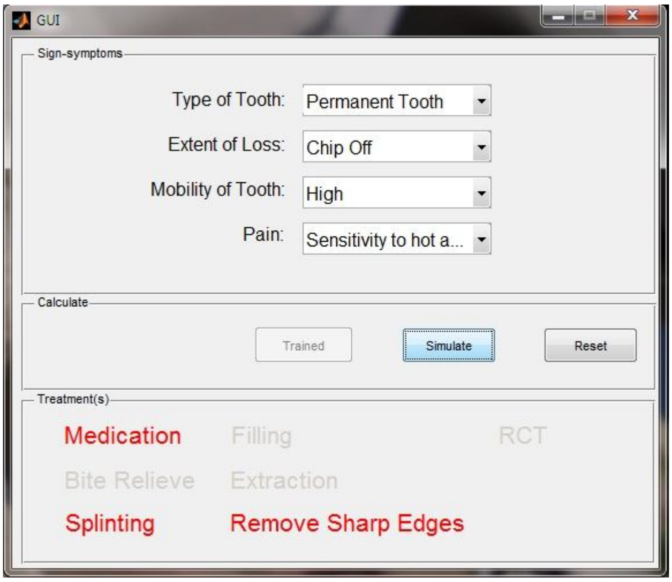
Where,

$$\delta_i^{(i-1)}(n) = \begin{Bmatrix} \phi'(net_i^{(i-1)})[d_i - y_i(n)], I = M \\ \phi'(net_i^{(i-1)})\sum_k w_{ki}\delta_k^{(i)}(n), 1 \le I \le M \end{Bmatrix}$$

Where $x_j(n)$ represents output of node j at iteration n, I is layer, k is the number of output nodes of neural network, M is output layer, ϕ is activation function. μ represent learning rate.

Implementation: We industrialized a matured Graphical User Interface (GUI). Dentists can submit the necessary information about a patient using this GUI. The result will be signposted in the form of a red color highlighted text of particular treatment. MATLAB is used for the development of the system. The GUI is shown in Fig. 2. As shown in Fig. 2, initially BPNN is trained with dataset containing information from 60 patients from a local dentist. After training of the network the inputs are selected from the drop-down list. *Permanent Tooth* is selected as type of tooth (age), *Chip off* is chosen as extend of tooth loss, mobility of tooth is *high* and pain is due to *Sensitivity to hold and cold*. The system suggests *medication*, *splinting*, and *remove sharp edges* as the treatment plans for this patient.

Fig. 2. GUI for decision making for treatment plan for broken tooth.



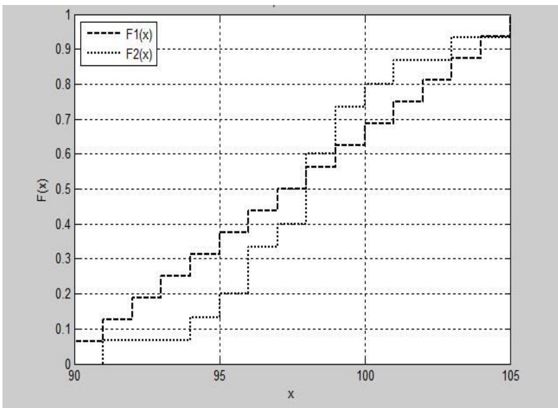
Evaluation: A questionnaire is distributed to ten dentists to collect their feedback. It shows only five sample data sets.

In the first case, the type of tooth is primary tooth, 2/3rd of crown is lost, mobility of tooth is high, sensitivity to hot and cold; the treatment suggested by the dentist is medication, splinting and filling of fractured tooth. The second case shows that if the type of tooth is primary tooth, full crown of tooth is lost, mobility of tooth is high and the pain is moderate then the treatment recommended by the system is medication, splinting and root canal treatment. The third case includes if the type of tooth is permanent tooth, 2/3rd of the tooth crown is lost, mobility of tooth is low, sensitivity to hot and cold then the treatments are medication, filling of the fractured tooth and root canal treatment. Finally, if the type of tooth is permanent tooth, full crown of tooth is lost, mobility is high, pain is moderate then the treatments should be medication and the extraction of fractured tooth. Kolmogorov–Smirnov (KS) test was used to compare the results produced by our system and the samples collected from the dentists. This statistical test is conducted to determine if two datasets differ significantly. The main advantage of this test is that it makes no assumption about the distribution of data, i.e., it is a non-parametric test. By comparing the observed results with the expected ones, one can decide whether the original hypothesis is valid. The null hypothesis in our case is that Expected and Observed vectors are from the same continuous distribution. The alternative hypothesis is that they are from different continuous distributions.

MATLAB Code to conduct KS test is as follows:

```
x1= 90:1:105;
Expected=
[98,98,98,98,98,98,98,98,98,98,98,98,98,98,98]
Observed=
[101,96,97,98,99,96,99,94,98,100,98,105,91,95,103
];
[h,p,k] = kstest2(Expected, Observed)
F1 = cdfplot(x1);
hold on
F2 = cdfplot(Observed)
```

Fig. 3. Comparison between the performance of the proposed system and dentists by using KS test (cumulative distribution function plots).



Results and discussion

The result shows that the performance of the system is closely matching with that of dentists, as shown in Fig. 3 (output of the MATLAB code). In this figure, F1 represents cumulative distribution of numbers [90, 105] and F2 represents the cumulative distribution of observation. The null hypothesis is that expected = observed. This hold true as $h = 0$, $p = 0.1359 > 0.05$ (default significance level) and $k = 0.40$.

Conclusion

We conclude that the results produced by the system are very appropriate and close to the actual results suggested by dentists. Although there are a number of fuzzy expert systems used in other medical domains, there is no similar system existing in dentistry so far. In this study, we mentioned only about the broken tooth and related treatments. But in future, the same work will be extended for other dental diseases and problems. A system based on such work can be a part of dentistry for the full assistance of dentists. It can also be used for the public so that they can get medical aid without visiting a dentist and can save money.

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