University of Sindh Journal of Information and Communication Technology
(USJICT)
Volume 3, Issue 1, January 2019

ISSN-E: 2523-1235, ISSN-P: 2521-5582
Website: http://sujo.usindh.edu.pk/index.php/USJICT/

Adaptive Neuro Fuzzy Inference System for Diagnosing Periodontitis

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Abstract— Periodontitis is a chronic inflammatory disorder that is caused by bacterial infection and leads to the destruction of the periodontium. Clinical diagnosis of periodontitis is quite difficult and most dentists' diagnosis might be subjective. Artificial intelligence has shown commendable results in medical diagnosis. This study utilized Adaptive Neuro Fuzzy Inference System in diagnosing periodontitis. 30 data instances were used in training the model. The system had a training error of 8.2725e-005 at epoch 1 and an average testing error of 3.1514.

Keywords: Periodontitis, Diagnosis, ANFIS

I. INTRODUCTION

Periodontitis is a bacterially induced disease that is characterized by a chronic inflammatory condition where the connecting tissue of the teeth is damaged. It is usually accompanied with gingivitis and loss of teeth towards the last stage of the disease [1,2]. In an elaborate study involving several nations on the prevalence of periodontitis, 5-15% of adult population are shown to have severe form of the disease. About 30-50% of adults are found to have moderate periodontitis while over 75% may be down with gingivitis [3].

Genetic and environmental factors have been suggested to lead to the development of this disease in addition to pathogenic microorganisms. The risk factors associated with periodontal disease include smoking, systemic diseases, steroid medications, lack of teeth, poor placement of dental bridges, dental crowding [4-6]; other factors such as HIV [7], diabetes and neutrophils disorders can also increase the risk of the disease [8].

Dentists use their experiences to make diagnosis of periodontitis on the basis of evaluation of clinical signs and symptoms (see below: section on ANFIS, Layer 1) and may be supported by evidence from X-rays.

Expertise of the dentists in the course of performing their functions vary and mainly subjective. There is the need therefore, for support systems to assist the dentist in predicting diseases accurately. Several computerized diagnotic systems have been devised to enhance clinicians' ability for accurate decision [9-10]. Studies have shown that Adaptive Neuro Fuzzy Inference System (ANFIS) is a very powerful tool in medical diagnosis and have produced excellent results [11-12]. ANFIS combines both neural network and fuzzy logic. The technique applied by ANFIS is quite simple. The fuzzy logic component maps each parameter in the dataset to linguistic labels for that parameter using a membership function which is used to keep track of input data to output data. The neural network component performs computational analysis on the dataset.

II. REVIEW OF RELATED WORKS

In recent past, researchers mostly used Artificial Neural Network (ANN) in diagnosing periodontal disease. Papantonopoulos and Takahashi [13] proposed an ANN that incorporated immunologic parameters. The ANN was trained using cross entropy value and was used to classify aggressive periodontitis patients. It was able to accurately classify 90% of aggressive periodontitis. In a similar study conducted by Shehnaz and Bhardwaj [14], they proposed a Convolutional Neural Network for diagnosing periodontal disease. The dataset used in training the network was collected from various medical laboratories. The dataset comprises of 437 data instances and five symptoms attribute which was collected using feature selection. The network was trained using multi-layer perception and a backward propagation learning algorithm. The system was able to accurately diagnose 93.5714% of periodontal cases.

Also Tran et al. [15] developed a fuzzy rule based system for dental diagnosis from x-ray. The experimental datasets used in their research were gotten from Hanoi Medical University, Vietnam and it contained 56 dental X- ray image cases. A feature extraction method was used to extract dental feature from the dental X-ray images. A fuzzy cluster mean algorithm was then used to classify the features into clusters and Mamdani inference model was used to generate the outcome. The outcome of the system was compared with the Fuzzy K-Nearest Neighbour

(FKNN). The results showed that their method had a better performance when compared to FKNN.

III. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

ANFIS is a hybrid system that comprises Neural Network (NN) and Fuzzy Logic (FL). It combines the computational capability of neural network and explanative power of fuzzy logic. Six layers make up the ANFIS architecture and are described below.

Layer 1: The symptoms for diagnosing periodontitis are the inputs used in this layer. These symptoms include: Swollen/puffy gums, Bright red, dusky red or purplish gums, Gums that feel tender when touched, Gums that bleed easily, Gums that pull away from the teeth (recede), making the teeth look longer than normal, developing new spaces between teeth, Pus between teeth and gums, Bad breath, Loose teeth, Pain when chewing and a change in the way your teeth fit together when you bite. However some redundant features were eliminated from the dataset using feature selection technique. This can be represented mathematically as shown in equation 1.

$$O_i^1 = x \qquad (1)$$

Layer 2: The layer contains a membership function which maps the symptom into a fuzzy set. A lot of membership functions exist but the bell membership function was employed for this research. The bell membership equation is shown in equation 2

$$\mu(x) = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \qquad (2)$$

where
a = the mean of parameter values
b = controls the slope of the curve of x at -b/2a, c-a, c+a, b/2a
c = centre of the curve
x= input from layer 1
$\mu =$ membership function of x

Layer 3: In this layer the fuzzified symptom values are combined using takagi sugeno inference model to generate an outcome for each case. This can be expressed mathematically as shown in equation 3.

$$O_i^3 = \mu(x) * \mu(y) \qquad (3)$$

Where
O_i^3 = is the i^{th} neuron output from layer 3
$\mu(x)$ and $\mu(y)$ $=$ membership function of x and y respectively

Layer 4: Each outcome from the preceding layer is normalized to produce an output for this layer. This could be represented mathematically as shown in equation 4

$$O_i^4 = \frac{O_i^3}{O_1^3 + O_2^3 + \cdots + O_n^3} \qquad (4)$$

Where
O_i^4 = is the i^{th} neuron output from layer
O_i^3 = is the i^{th} neuron output from layer 3
n= total number of neuron in layer 4

Layer 5: The outcome from this layer is produced by multiplying the outcome of the preceding layer by the output from layer 2. This could be represented mathematically as shown in equation 5

$$O_i^5 = O_i^4(p_i(x) + q_i(y) + r) \qquad (5)$$

Where
O_i^5 = is the i^{th} neuron output from layer 5
p_i , q_i = consequent parameters
r= bias

Layer 6: The neuron in this layer produces the overall output of the system by summing up the values in layer 5. This can be represented mathematically as shown in equation 6

$$O_i^6 = \sum_i^n O_i^5 \qquad (6)$$

Where
O_i^6 = is the i^{th} neuron output from layer 6
O_i^5 = is the i^{th} neuron output from layer 5

IV. EXPERIMENT AND RESULTS

The dataset used in this study comprises of 45 diagnosed data instances. It was collected from Dental Clinic of the University of Benin Teaching Hospital, Benin City. Approximately 67% (30 cases) of the dataset was used in training of the system while the remaining 33% (15 cases) were used in testing the system. The ANFIS model have 5 inputs - Symptom1, Symptom2, Symptom3, Symptom4 and Symptom5 corresponding to swollen gum, gums that bleed easily, loose teeth, pus between teeth and gum and painful chewing respectively. Matrix Laboratory (MATLAB) version 7.5.0 (R2007b) was used to implement the ANFIS model. The ANFIS model was designed using Gaussian Membership function; this is because studies have shown that it generates the best results [16-17]. The membership function for each linguistic variable has three (3) linguistic labels which are; mild, moderate and severe. The system had 243 fuzzy rules in the rule layer. The model utilizes a hybrid optimization method with an error tolerance of 0.05. The ANFIS model was trained for 20 epochs. The result realized from training the model showed that the system had a training error of 8.2725e-005 at epoch 1 and an average testing error of 3.1514 on the test dataset, which indicates that the model was accurately able to classify approximately 96% of the test dataset. Figure 1, Figure 2, Figure 3, Figure

4, Figure 5 and Figure 6 show the ANFIS architecture, fuzzy inference engine, membership function for the linguistic variables, training dataset, training process and testing process respectively. The surface view diagrams were generated at the end of the training process and are clearly shown in figures 7a, 7b, 7c, 7d, 7e

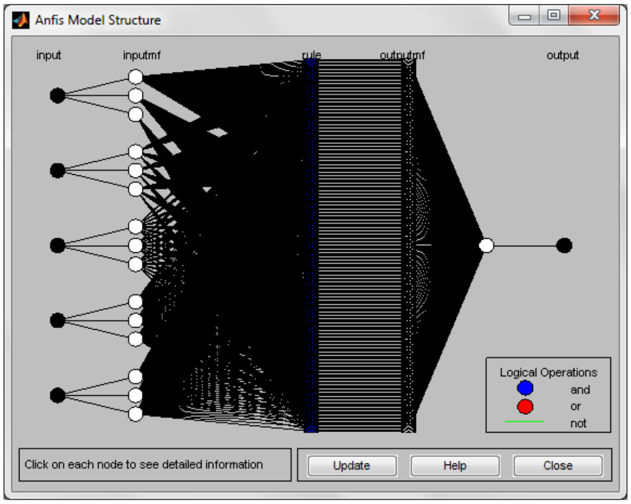

Figure 1 Adaptive Neuro Fuzzy Inference System (ANFIS) Architecture

Figure 1 shows the architecture of the Adaptive Neuro Fuzzy Inference System model. It has five inputs which are swollen gum, gums that bleed easily, loose teeth, pus between teeth and gum and painful chewing. These were the symptoms used in diagnosing periodontitis

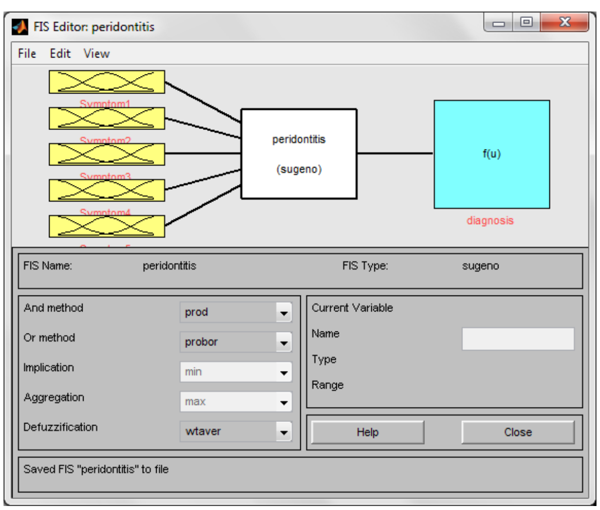

Figure 2 Fuzzy Inference Engine

Figure 2 shows the fuzzy inference engine. The fuzzy inference engine contains the fuzzification layer, rule layer and defuzzification layer.

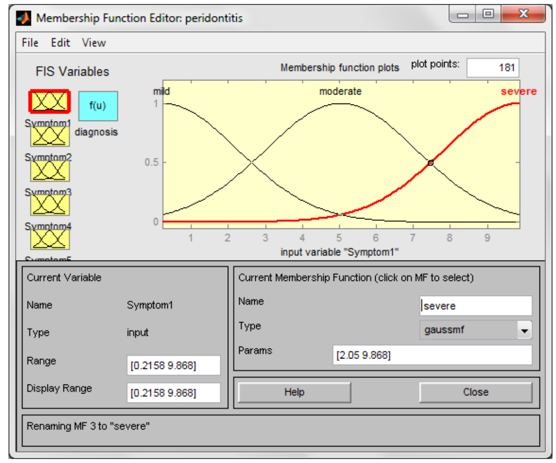

Figure 3 Membership Function for Linguistic Variable

Figure 3 shows the membership function used in mapping symptom1 values into fuzzy sets. The Gaussian membership function was used to map the symptoms into fuzzy set.

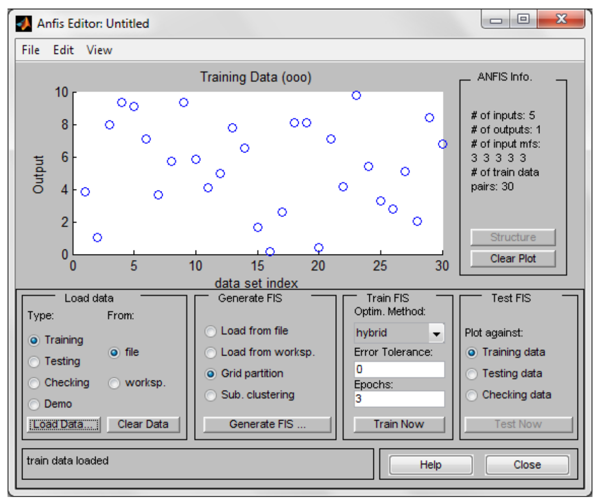

Figure 4 Training Dataset Set Loaded into the ANFIS

Figure 4 shows the data used in training the ANFIS model. 30 cases was used to train the ANFIS model

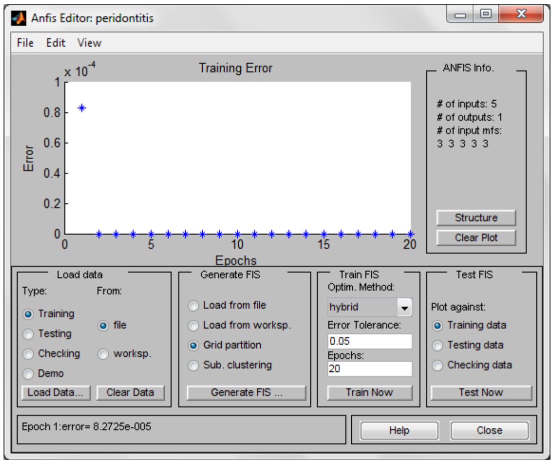

Figure 5 Training Process

Figure 5 shows the training process of the ANFIS model. The Model was trained for 30 epochs with an error tolerance of 0.05

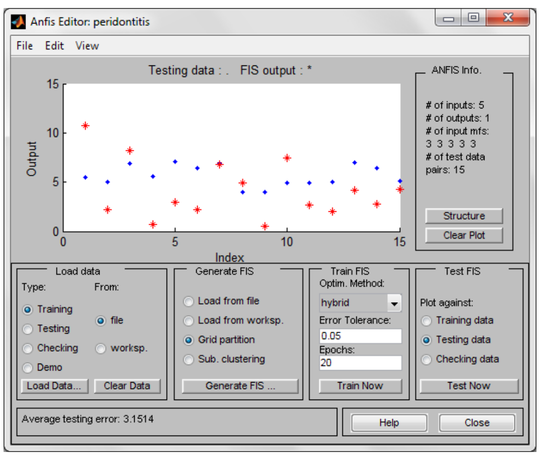

Figure 6 Testing process of the ANFIS model

Figure 6 shows the testing process of the ANFIS model. The system had an average testing error of 3.1514 on the 15 test cases used to train the ANFIS model.

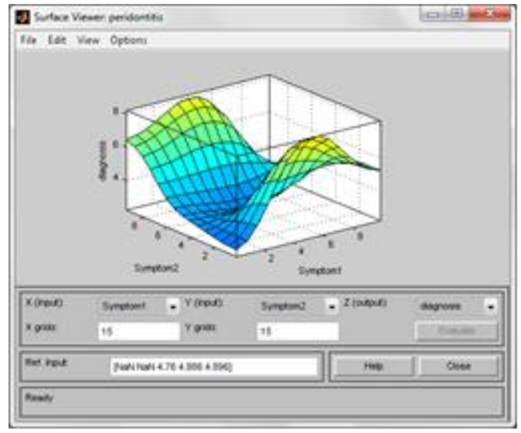

Figure 7a shows the relationship between symptom 1 (swollen gum) and symptom 2 (gum that bleed easily) to the diagnosis of periodontitis.

Figure 7a shows that the diagnosis of periodontitis is high when symptom-1 falls between 4 and 8 and symptom-2 falls between 6 and 10. The part of the surface view chart indicated with yellow shows high value for periodontitis while the part indicated with blue shows low value for periodontitis.

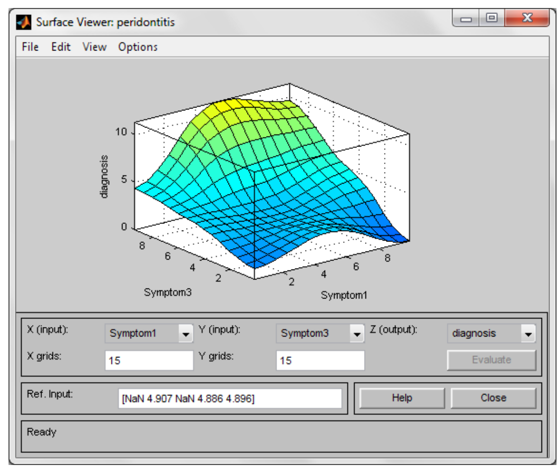

Figure 7b shows the relationship between symptom 1 (swollen gum) and symptom 3 (loose teeth) to the diagnosis of periodontitis

Figure 7b shows that the diagnosis of periodontitis is high when symptom-1 and symptom-3 increases. The part of the surface view chart indicated with yellow shows high value for periodontitis while the part indicated with blue shows low value for periodontitis.

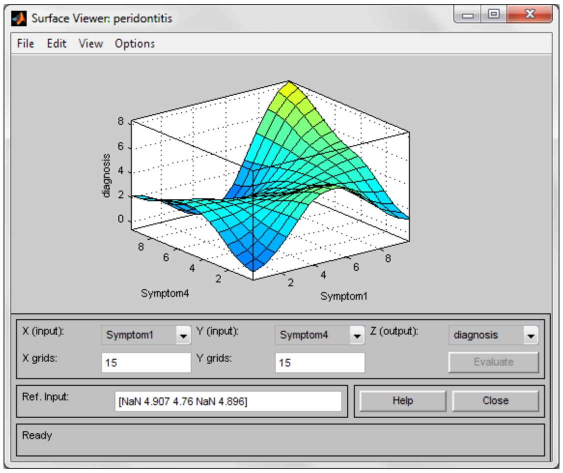

Figure 7c shows the relationship between symptom 1 (swollen gum) and symptom 4 (pus between teeth and gum) to the diagnosis of periodontitis

Figure 7c shows that the diagnosis of periodontitis is high when symptom-4 falls between 6 and 10 and symptom-4 falls between 6 and 10. The part of the surface view chart indicated with yellow shows high value for periodontitis while the part indicated with blue shows low value for periodontitis.

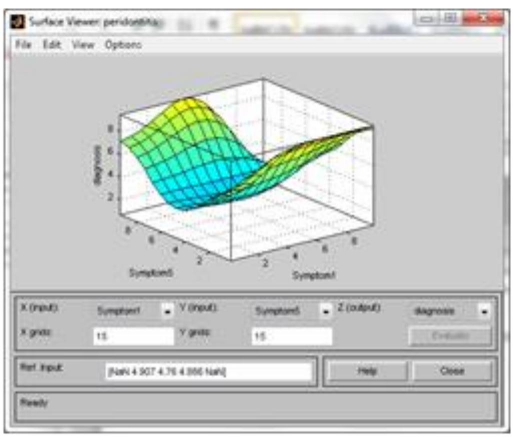

Figure 7d shows the relationship between symptom 1 (swollen gum) and symptom 5 (painful chewing) to the diagnosis of periodontitis

Figure 7d shows that the diagnosis of periodontitis is high when symptom-1 falls between 0 and 10 and symptom-5 falls between 6 and 10. The part of the surface view chart indicated with yellow shows high value for periodontitis while the part indicated with blue shows low value for periodontitis.

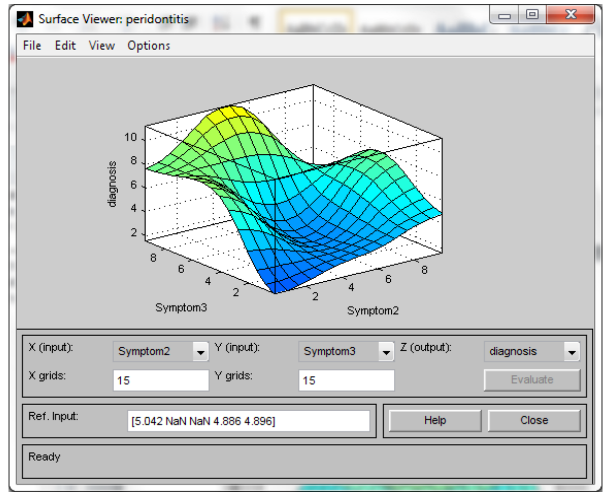

Figure 7e shows the relationship between symptom 2 (swollen gum) and symptom 3 (loose teeth) to the diagnosis of periodontitis

Figure 7e shows that the diagnosis of periodontitis is high when symptom-3 falls between 6 and 10 and symptom-2 falls between 4 and 6. The part of the surface view chart indicated with yellow shows high value for periodontitis while the part indicated with blue shows low value for periodontitis.

V. DISCUSSION

In this study an ANFIS model was developed for diagnosing periodontitis. Five symptoms (swollen gum, painful chewing, loose teeth, gum that bleed easily and pus between teeth and gum) were used in predicting periodontitis with this ANFIS model. The relationship between the symptoms and the diagnosis of periodontitis are shown clearly in figures 7a -7e. The ANFIS model had a prediction accuracy of 96.9%. Significant amount of research has been conducted on periodontal disease diagnosis [13-15]. Our study validates the assertions by Shehnaz and Bhardwaj [14] in which clinical symptoms were used to develop the Artificial Neural Network, although their technique significantly differed from ours. The takagi sugeno model which was used to model the rule layer of the ANFIS system is quite different from the method used in the Fuzzy Rule-Based Systems [15] where they employed the mamdani fuzzy inference system. Our model combines both neural network and fuzzy logic and this makes it more powerful than Artificial Neural Network employed by Shehnaz and Bhardwaj [14] and Fuzzy Cluster Mean employed by Tran et al. [15]. Nevertheless, the studies generated commendable results in the diagnosis of periodontitis. However the outcome from our study has shown that ANFIS is better compared to ANN and the Fuzzy Cluster Mean as regards the outcomes of 96.9% as to 93.5714% and 90.29% diagnostics accuracy of periodontal cases respectively.

VI. CONCLUSIONS

In this paper we designed an ANFIS structure for diagnosing periodontitis and it yielded an excellent result. The ANFIS model had a prediction accuracy of 96.9%, which is higher than other models utilized in diagnosing periodontitis. The implementation of this ANFIS framework will assist the dentist in periodontal diagnosis. Further research should be geared towards designing a more sophisticated neuro fuzzy model that can accommodate larger clinical symptom base as it may help in a more accurate diagnosis.

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