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# Automatic diagnosis of diabetes using adaptive neuro-fuzzy inference systems

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**Abstract:** *A new approach based on an adaptive neuro-fuzzy inference system (ANFIS) is presented for diagnosis of diabetes diseases. The Pima Indians diabetes data set contains records of patients with known diagnosis. The ANFIS classifiers learn how to differentiate a new case in the domain by being given a training set of such records. The ANFIS classifier is used to detect diabetes diseases when eight features defining diabetes indications are used as inputs. The proposed ANFIS model combines neural network adaptive capabilities and the fuzzy logic qualitative approach. The conclusions concerning the impacts of features on the diagnosis of diabetes disease are obtained through analysis of the ANFIS. The performance of the ANFIS model is evaluated in terms of training performances and classification accuracies and the results confirm that the proposed ANFIS model has potential in detecting diabetes diseases.*

***Keywords:*** adaptive neuro-fuzzy inference system (ANFIS), fuzzy logic, diabetes diagnosis

## 1. Introduction

The main concept of medical technology is an inductive engine that learns the decision characteristics of diseases and can then be used to diagnose future patients with uncertain disease states (Übeyli, 2007, 2008, 2009a). This is where fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. Fuzzy sets have attracted growing attention and interest in modern information technology, production techniques, decision making, pattern recognition, diagnostics, data analysis etc. (Dubois & Prade, 1998; Kuncheva & Steimann, 1999; Nauck & Kruse, 1999). Neuro-fuzzy systems are fuzzy systems which use artificial neural networks theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of two paradigms, fuzzy logic and artificial neural networks, by utilizing the mathematical properties of artificial neural networks in tuning rule-based fuzzy systems that approximate the way man processes information. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modelling nonlinear functions. In the ANFIS, the membership function parameters are extracted from a data set that describes the system behaviour. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion (Jang, 1992, 1993). Successful implementations of the ANFIS in biomedical engineering have been reported for classification (Usher *et al.*, 1999; Belal *et al.*, 2002; Übeyli, 2008, 2009b, 2009c, 2009d) and data analysis (Virant-Klun & Virant, 1999).

In this study, a new approach based on the ANFIS is presented for the diagnosis of diabetes diseases. The ANFIS classifier is used to diagnose diabetes disease when eight features defining diabetes indications are used as inputs. The Pima Indians diabetes data set (Pima Indians diabetes database, http://www.cormactech.com/neunet) is analysed by the ANFIS. The proposed ANFIS model is then evaluated and its performance is reported. We are able to achieve significant improvement in accuracy by applying the ANFIS model. Finally, some conclusions are drawn concerning the impacts of features on the diagnosis of diabetes disease.

## 2. Database overview

Diabates is a metabolic disease in which there is a deficiency or absence of insulin secretion by the pancreas. Diabetes occurs in two major forms: type I or insulin-dependent diabetes, and type II or non-insulin-dependent diabetes. Most studies of the age of onset of type I diabetes have been restricted to children and adults under 30 years old. The age distributions in females and males show small differences which have been most clearly demonstrated in surveys in children and young adults. Both genders are affected, but in many communities the majority with type II diabetes are female. The prevalence of type II diabetes rises with increasing age and in many populations the majority of those with diabetes are either middle-aged or elderly. Diabetes may be considered as a disorder of the metabolic disposal of food. The interaction of food and diabetic state must be assessed from two aspects: first, whether food precipitates the diabetic condition, and second, the type of food that is most appropriate for the person with established diabetes, whether it is insulin-dependent or non-insulin-dependent. Diabetes shows considerable familial aggregation which may result from either the inheritance of disease susceptibility or the sharing of a common environment by members of the same family. Therefore, it is important to determine the existence of diabetes in families of the subjects. The occurrence of gestational diabetes, which either first appears or is first recognized during pregnancy, is associated with increased risk for the development of diabetes in subsequent years. Thus, women who experience gestational diabetes should be considered a high risk group for the development of type II diabetes (Besser *et al.*, 1988; Balkau *et al.*, 2007; Cefalu, 2008; Clark, 2008; McGill *et al.*, 2008; Misra & Lager, 2008; Streja, 2008). In this study, the Pima Indians diabetes database (http://www.cormactech.com/neunet) was analysed. The data consist of 768 records and, according to the examination results, 268 of them are diabetics and the rest of them are non-diabetics. Each record has eight attributes and these are detailed in Table 1. In particular, all patients in the database are females at least 21 years old of Pima Indian heritage. Eight independent input parameters, essentially risk factors for diabetes, are incorporated in the classifiers (Übeyli, 2007, 2009a).

## 3. Adaptive neuro-fuzzy inference system (ANFIS)

### 3.1. Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1992, 1993). Such a framework makes ANFIS modelling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if–then rules based on a first-order Sugeno model are considered:

$$\textbf{Rule 1:}\ \text{If}\ (x\ \text{is}\ A_1)\ \text{and}\ (y\ \text{is}\ B_1)\ \text{then}\ (f_1 = p_1 x + q_1 y + r_1)$$

$$\textbf{Rule 2:}\ \text{If}\ (x\ \text{is}\ A_2)\ \text{and}\ (y\ \text{is}\ B_2)\ \text{then}\ (f_2 = p_2 x + q_2 y + r_2)$$

where $x$ and $y$ are the inputs, $A_i$ and $B_i$ are the fuzzy sets, $f_i$ are the outputs within the fuzzy region specified by the fuzzy rule, and $p_i$, $q_i$ and $r_i$ are the design parameters that are

**Table 1:** *Pima Indians diabetes database: description of attributes*

| *Attribute number* | *Attribute description* | *Mean* | *Standard deviation* |
|---|---|---|---|
| 1 | Number of times pregnant | 3.8 | 3.4 |
| 2 | Plasma glucose concentration a 2 hour oral glucose tolerance test | 120.9 | 32.0 |
| 3 | Diastolic blood pressure (mmHg) | 69.1 | 19.4 |
| 4 | Triceps skin fold thickness (mm) | 20.5 | 16.0 |
| 5 | 2-hour serum insulin (μU/ml) | 79.8 | 115.2 |
| 6 | Body mass index (weight in kg/(height in m)$^2$) | 32.0 | 7.9 |
| 7 | Diabetes pedigree function | 0.5 | 0.3 |
| 8 | Age (years) | 33.2 | 11.8 |

$N = 768$ observations, 268 diabetics and 500 non-diabetics.

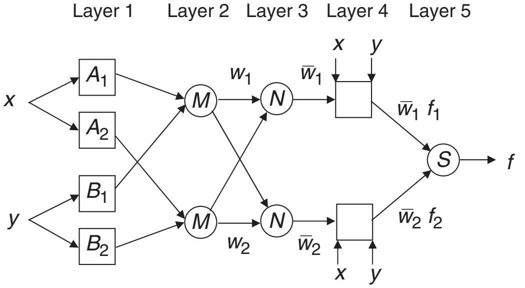


**Figure 1:** *ANFIS architecture.*

determined during the training process. The ANFIS architecture to implement these two rules is shown in Figure 1, in which a circle indicates a fixed node whereas a square indicates an adaptive node.

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grades of the inputs, which are given by

$$O_i^1 = \mu_{A_i}(x) \quad i = 1, 2 \tag{1}$$

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3, 4 \tag{2}$$

where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership function is employed, $\mu_{A_i}(x)$ is given by

$$\mu_{A_i}(x) = \frac{1}{1 + \{[(x - c_i)/a_i]^2\}^{b_i}} \tag{3}$$

where $a_i$, $b_i$ and $c_i$ are the parameters of the membership function, governing the bell-shaped functions accordingly.

In the second layer, the nodes are fixed nodes. They are labelled $M$, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1, 2 \tag{4}$$

which are the so-called firing strengths of the rules.

The nodes in the third layer are also fixed nodes. They are labelled $N$, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \tag{5}$$

which are the so-called normalized firing strengths.

In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1, 2 \tag{6}$$

In the fifth layer, there is only one single fixed node labelled $S$. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_i^5 = \sum_{i=1}^{2} \bar{w}_i f_i = \frac{\left(\sum_{i=1}^{2} w_i f_i\right)}{w_1 + w_2} \tag{7}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first-order polynomial. These parameters are so-called consequent parameters (Jang, 1992, 1993).

### *3.2. Learning algorithm of the ANFIS*

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ and $\{p_i, q_i, r_i\}$, to make the ANFIS output match the training data. When the premise parameters $a_i$, $b_i$ and $c_i$ of the membership function are fixed, the output of the ANFIS model can be written as

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{8}$$

Substituting equation (5) into equation (8) yields

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{9}$$

Substituting the fuzzy if–then rules into equation (9), it becomes

$$\begin{aligned} f = {} & \bar{w}_1 (p_1 x + q_1 y + r_1) \\ & + \bar{w}_2 (p_2 x + q_2 y + r_2) \end{aligned} \tag{10}$$

After rearrangement, the output can be expressed as

$$\begin{aligned} f = {} & (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1) r_1 \\ & + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2) r_2 \end{aligned} \tag{11}$$

which is a linear combination of the modifiable consequent parameters $p_1$, $q_1$, $r_1$, $p_2$, $q_2$ and $r_2$. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust the premise parameters corresponding to the fuzzy sets in the input domain optimally. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proved that this hybrid algorithm is highly efficient in training the ANFIS (Jang, 1992, 1993). Recently, this architecture was used in previous studies related to biomedical applications (Übeyli, 2008, 2009b, 2009c, 2009d).

## 4. Results and discussion

The collection of well-distributed, sufficient and accurately measured input data is the basic requirement to obtain an accurate model. New methods have been developed for computer decision making in medicine and to evaluate these methods critically in clinical practice. Neural networks have been used in different medical diagnoses and the results were compared with physicians' diagnoses and existing classification methods (Shanker, 1996; Lim *et al.*, 1997; Park & Edington, 2001; Übeyli, 2007). Many of these authors found that neural networks have more flexibility in modelling and reasonable accuracy in prediction. What makes neural networks a promising tool is their capacity to find near-optimum solutions from limited or incomplete data sets and the fact that learning is accomplished through training. In addition to these characteristics, it has been shown that neural networks can combine data of a different nature in one system, such as data derived from clinical protocols and laboratory data obtained from measurements and features from signals and images, thus forming an integrated diagnostic system (Tafeit & Reibnegger, 1999; Usher *et al.*, 1999; Virant-Klun & Virant, 1999; Belal *et al.*, 2002; Übeyli, 2007, 2008, 2009a, 2009b, 2009c, 2009d). The proposed ANFIS classifier can be a useful tool in the diagnosis of diabetes according to the given risk factors.

The data set consisting of eight features is summarized in Table 1. The proposed technique involved training the ANFIS classifier to diagnose diabetes disease when the features given in Table 1 were used as inputs. There are a total of 768 records in the Pima Indians diabetes database, of which 268 are diabetics and 500 are non-diabetics. In the classifiers, 284 of 768 records were used for training and the rest for testing. The training set consisted of 136 diabetics and 148 non-diabetics. The testing set consisted of 132 diabetics and 352 non-diabetics. Samples with target outputs (diabetic and non-diabetic) were given the binary target values of (0, 1) and (1, 0), respectively. The training data set was used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the diagnosis of diabetes disease. The ANFIS used 284 training data in 600 training periods and the step size for parameter adaptation had an initial value of 0.011. The steps of parameter adaptation of the ANFIS are shown in Figure 2. At the end of 600 training periods the network error (mean square error, MSE) convergence curve of the ANFIS was derived, as shown in Figure 3. From the curve, the final convergence value is $3.3054 \times 10^{-5}$.

In the classification studies, all of the features used in the descriptions of instances may have different levels of relevance. Feature saliency provides a means for choosing the features which are best for classification. Therefore, in the present study changes of the final (after training) generalized bell-shaped membership functions with respect to the initial (before training) generalized bell-shaped membership functions of the input parameters were examined. The membership function of each input parameter was divided into three regions, namely small, medium and large. The examination of initial and final membership functions indicates that there are considerable changes in the final membership functions of the eight features. Figures 4 and 5 show the initial and final membership functions of input 3 (diastolic blood pressure) and input 6 (body mass index) respectively using the generalized bell-shaped membership function. Based on the analysis of membership functions of each input feature, it was found that all of the eight inputs have saliency in diabetes diagnosis.

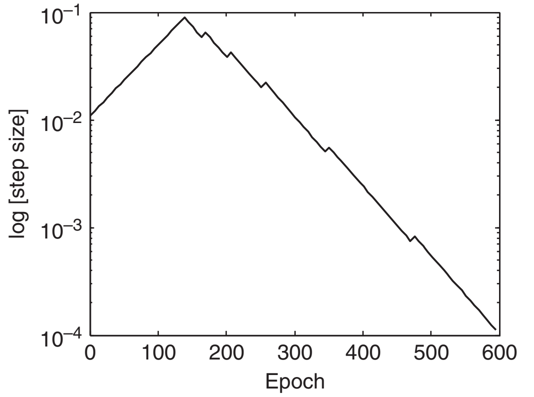


**Figure 2:** *Adaptation of parameter steps of the ANFIS.*

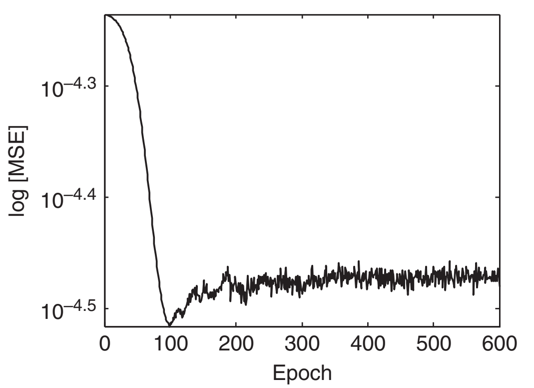


**Figure 3:** *The curve of network error convergence of the ANFIS.*

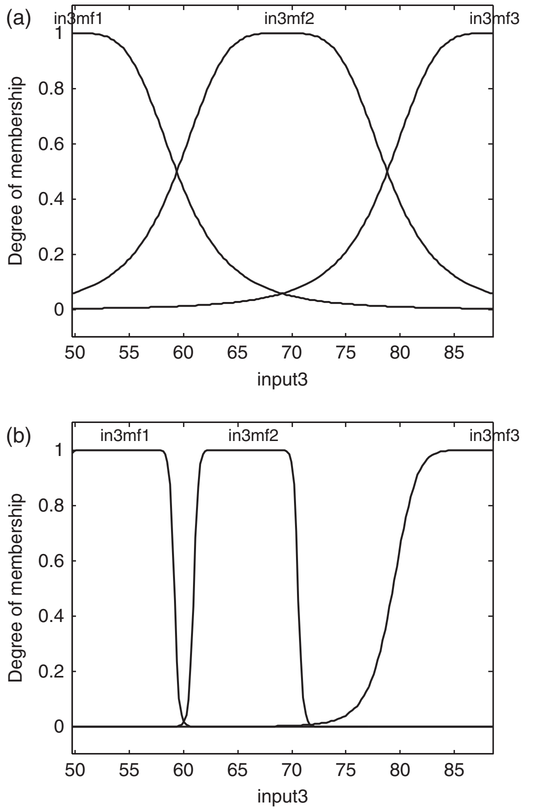


**Figure 4:** *(a) Initial and (b) final generalized bell-shaped membership function of input 3 (diastolic blood pressure).*

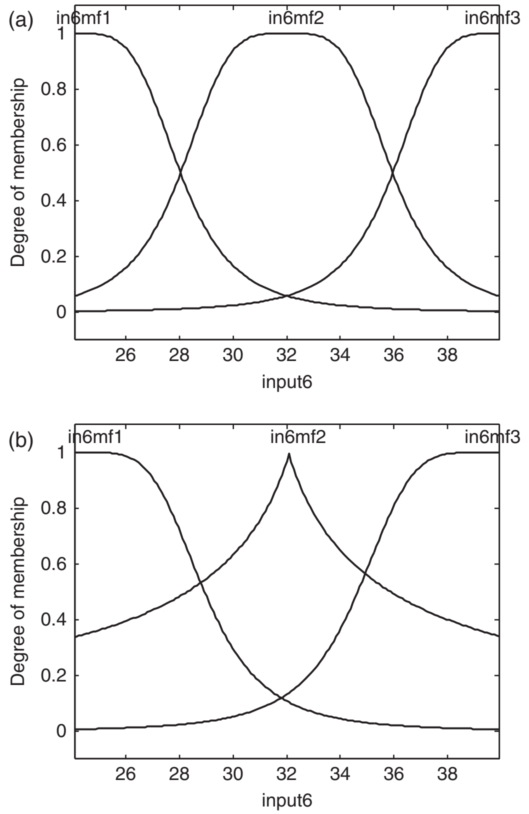


**Figure 5:** *(a) Initial and (b) final generalized bell-shaped membership function of input 6 (body mass index).*

After training, 484 testing data were used to validate the accuracy of the ANFIS model for diagnosis of diabetes. Classification results of the classifiers were displayed with a confusion matrix. In a confusion matrix, each cell contains the raw number of exemplars classified for the corresponding combination of desired and actual network outputs. The confusion matrix showing the classification results of the ANFIS used for diagnosis of diabetes is given in Table 2. From this matrix one can tell the frequency with which a record is misclassified as another.

The test performance of the classifiers can be determined by the computation of specificity, sensitivity and total classification accuracy. The specificity, sensitivity and total classification accuracy are defined as

**Table 2:** *Confusion matrix*

| | *Output result* | |
|---|---|---|
| *Desired result* | *Non-diabetics* | *Diabetics* |
| Non-diabetics | 347 | 4 |
| Diabetics | 5 | 128 |

*Specificity:* the number of true negative decisions/the number of actually negative cases
*Sensitivity:* the number of true positive decisions/the number of actually positive cases
*Total classification accuracy:* the number of correct decisions/the total number of cases

A true negative decision occurs when both the classifier and the physician suggest the absence

**Table 3:** *The values of the statistical parameters (%)*

| *Specificity* | *Sensitivity* | *Total classification accuracy* |
|---|---|---|
| 98.58 | 96.97 | 98.14 |

of a positive detection. A true positive decision occurs when the positive detection of the classifier coincides with a positive detection of the physician.

The values of the statistical parameters (sensitivity, specificity and total classification accuracy) are given in Table 3. The total classification accuracy of the ANFIS model was 98.14%.

## 5. Conclusions

This paper presented an application of the ANFIS for diagnosis of diabetes disease. Fuzzy set theory plays an important role in dealing with uncertainty when making decisions in medical applications. The use of fuzzy logic enabled us to use the uncertainty in the classifier design and consequently to increase the credibility of the system output. The ANFIS classifier was used to diagnose diabetes when eight features defining diabetes disease were used as inputs. The presented ANFIS model combined neural network adaptive capabilities and the fuzzy logic qualitative approach. The classification results and statistical measures were used for evaluating the ANFIS. The total classification accuracy of the ANFIS model was 98.14%. The results obtained demonstrated that the proposed ANFIS model can be used to diagnose diabetes by taking into consideration the misclassification rates.

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