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The Diagnosis of Diabetic Nephropathy using Neuro-Fuzzy Expert System

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Abstract

Objectives: To develop an improved expert system for the diagnosis of nephropathy. **Methods/Statistical Analysis**: To achieve this objective, data on the nephropathy is taken by specialist doctors in this domain and adaptive neuro-fuzzy technique is applied on it. Gaussian membership functions are attempted in the study and MATLAB is used to implement the expert system. **Findings:** This system succeeds up to 96.25% of the cases. The sensitivity, specificity and precision obtained from this system are 97.5%, 95% and 95.12%. These parameters are found out by comparing the output achieved from this system with the judgments made by experts in this area. **Application/Improvements:** This expert system can be applied in the situations where the patient is unable to get medical assistance from doctor due to certain problems like low ratio of doctor to patient, unavailability of doctors in undeveloped areas etc.

Keywords: Diagnosis, Expert System, Nephropathy, Neuro-Fuzzy

1. Introduction

There is an increased burden of diabetes in developing countries. The largest number of diabetics in the world is present in India with frequency of 11.8% in urban and 3.8% in rural adults. Both the type 1 and type 2 diabetes direct to end stage renal disease. The reason behind this is the delayed detection of nephropathy in patients having diabetes. Nephropathy can be controlled by early recognition and treatment of renal changes[1,2]. In early detection of nephropathy, the expert may recommend the suitable actions to reduce the risk of nephropathy, adopt the multifactorial interventions and use the agents with renoprotective effect. So the early detection of diabetic nephropathy is must for the longer survival of patients. But due to contradictory information, the diagnosis of disease is overwhelming task in some cases[3,4]. For example some symptoms lead to different interpretations. The diagnosis in these cases is quite difficult. Hence the expert also needs some help to make the right diagnosis[5]. In some cases, some symptoms of the disease are very much common and some symptoms are very alike. It again produces difficulty for the expert to make the diagnosis[6]. The medical expert systems are built to aid the experts to reach at the right diagnosis[7].

The medical expert systems are made up of programs and medical knowledge base. The knowledge about the disease is contained in the knowledge base[8]. In simple rule based medical expert systems, the user is asked to answer yes or no if a particular symptom occurs or not. In the end, on account of user's answers name of the disease is found out[9]. Fuzzy medical expert systems are grouping of rules and membership functions. Fuzzy systems are sloping towards mathematical processing[10,11]. Fuzzy logic is a developing tool for its modeling using real values taken from structured range. It is likely to maintain as many features of classical logic as feasible[12]. Fuzzy logic is a data processing methodology that is highly advisable when trying to model imprecise information and to make rational decisions in an uncertainty environment[13]. The fuzzy expert system is based on three walks. In the first walk, the non fuzzy set is transformed into fuzzy

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set. It is known as fuzzification[14]. In the second walk, the input fuzzy set is converted into output fuzzy set. In the third walk, the fuzzy set value is converted into concrete value[10]. Mamdani fuzzy system is broadly acknowledged for confining skilled knowledge. It consents to illustrate the knowledge in extra perceptive way. Mamdani fuzzy system employs the method of defuzzification of a fuzzy outcome. Because of the perceptive environment of the rule base, the decision support applications widely use mamdani fuzzy system. Mamdani fuzzy system is inflexible in a design phase of a system[15]. In sugeno fuzzy system, the crisp output is calculated by using weighted average method. Therefore the defuzzification procedure is bypassed in sugeno fuzzy system. Sugeno fuzzy system has no output membership functions. Sugeno technique is computationally proficient and works healthy with adaptive and optimization procedures, which builds it very striking in direct problems.

The optimization and adaptive procedures are able to adapt the membership functions so that fuzzy expert system finest forms the data. Neuro-fuzzy system being an adaptive technique is a grouping of fuzzy logic with neural network. This hybrid system can be more efficient[16,17]. Hence the solving method is adaptive neuro-fuzzy expert system. In adaptive neuro-fuzzy expert system, firstly data is collected from the experts in medical assessments on patients and using this input output data deposit, fuzzy inference system is built whose membership function factors are adjusted by means of back propagation technique or in grouping with least square type of method[18].

2. Background Work

Several clinical problems are diagnosed by classification system. Diabetic nephropathy is also one among them. There are several studies for the diagnosis of diabetic nephropathy. Rama devi has designed fuzzy knowledge based system to identify the risk of diabetic nephropathy. This system helps to resolve the renal failure and protects the patient from ESRD. Narasimhan proposed fuzzy logic system for the diabetic nephropathy control and obtained various parameters like classification accuracy, sensitivity and specificity[18,19]. Meza-Palacios has developed a fuzzy inference system for the assessment of diabetic nephropathy. This fuzzy inference system succeeds in up to 93.33% of the cases[20].

3. The Problem

The incidence of diabetic nephropathy is rising at an alarming rate. The numeral of people living with this disease is increasing due to population growth, hypertension, smoking and lack of expert guidance. The ratio of doctor to patient is very small. Patient does not get expert medical assistance. Mostly patients recognize the nephropathy in last stages of renal disease. Sometimes doctors are also unable to diagnose diabetic nephropathy in early stages as some symptoms lead to different interpretations. So, medical expert systems are required to remove these problems. Simple rule based medical expert systems have drawback that they do not tell the probability the diagnosis is close to reality and development of rules. For example a simple rule based system is built for the finding of diabetic nephropathy. The knowledge base for the system is having knowledge of diabetic nephropathy. The rule developed from the knowledge taken from expert is in the following form:

Disease (Patient, nephropathy):-
Symptom (Patient, glomerular_filtration_rate),
Symptom (Patient, serum_creatinine),
Symptom (Patient, blood_glucose),
Symptom (Patient, type2_diabetes_mellitus_age),
Symptom (Patient, uric_acid),
Symptom (Patient, hypertension),
Symptom (Patient, dyslipedemia).

The system will ask to the user about the symptoms and user will reply yes or no to the symptoms. If the user will reply yes to all the symptoms of a particular disease then that disease will be diagnosed by the system. As in the above rule, if user will reply yes to glomerular filtration rate, serum creatinine, blood glucose, type2_diabetes_mellitus_age, uric_acid, hypertension and dyslipedemia then the system will find out that the patient is having diabetes nephropathy and in case user replies no to any one or more symptoms then the system will be unable to diagnose. So in this way, the simple rule based expert systems do not calculate the probability of disease and there is a need to formulate the rules from the knowledge taken from expert.

The fuzzy medical expert systems tell the probability of disease that is close to reality but the drawback of fuzzy systems is to choose and develop the membership functions and rules. It is an important issue in fuzzy modeling. For instance the fuzzy inference system for analysis of diabetes has input parameter 'glomerular filtration rate'. It is divided into three linguistic terms which are moderate, minor and normal. Using fuzzy system, there is a need to formulate the membership functions and rules. The membership function for glomerular filtration rate is chosen as follow[21] in Figure 1.

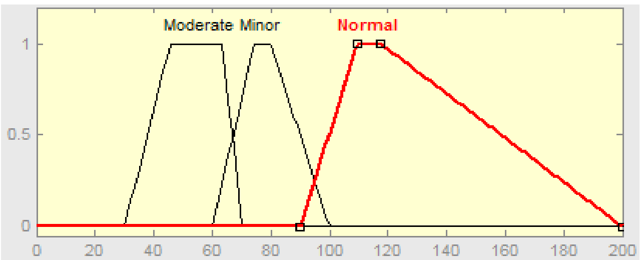

Figure 1. Membership functions for glomerular filteration rate.

Example of rule created with the expertise of doctor is as follow:

If GFR is normal and blood glucose is good and T2DMA is in stage 1 and uric acid is good and serum creatinine is good and no hypertension and no dyslipidemia THEN the patient has good nephropathy control.

So to remove these drawbacks, we have used adaptive neuro-fuzzy technique for the diagnosis of diabetic nephropathy. In this technique, the membership functions and rules are generated automatically.

4. The Idea

The idea is to apply the neuro-fuzzy technique for the diagnosis of diabetic nephropathy. The true idea for this paper comes out from the following research papers:

"Development of a fuzzy expert system for the nephropathy control assessment in patients with type 2 diabetes mellitus" by Ramiro Meza-Palacios, Alberto A. Aguilar-Lasserre, Enrique L. Urena-Bogarin, Carlos F. Vazquez-Rodriguez, Ruben Posada-Gomez, Armin Trujillo-Mata. They have diagnosed diabetic nephropathy using fuzzy expert system[21]. From this paper, we identify the inputs and output for the nephropathy control medical diagnostic system. We have taken the same inputs and output in our research work.

"Comparison of fuzzy logic and Neuro fuzzy algorithms for air conditioning system" by Arshdeep kaur, Amrit kaur. They have applied fuzzy and neuro-fuzzy techniques for air conditioning system and found that the neuro-fuzzy technique is superior to fuzzy logic[22]. From here we come to know that the neuro-fuzzy technique is superior to fuzzy logic and applied this neuro-fuzzy technique for diagnosis of diabetic nephropathy in our research work.

"Neuro-fuzzy expert system for breast cancer diagnosis" by Manisha arora, Dinesh tagra. They have applied neuro-fuzzy technique with gaussian membership functions in their research work and they have obtained better results with this[11]. From this, we come to know that the gaussian membership functions are better than others. So we have used Gaussian membership functions in our research work.

5. The Details

Neuro-fuzzy algorithm for diagnosis of diabetic nephropathy is developed using ANFIS edit in MATLAB. A sample of dataset taken from experts in medical assessments on patients of diabetic nephropathy is shown in Table 1.

Further fuzzy expert system is generated through seven inputs plus one output. The seven inputs take the

Table 1. A sample of dataset taken from experts

S No.	GFR	BG	T2DMA	UA	SC	HYP	DLP	Nephropathy control
1	61.06	130	8	5.4	0.7	1	0	2
2	89.41	121	3	6.1	1.2	0	0	3
3	111.7	337	23	4.7	0.7	1	1	4
4	64	125	2	7.3	1.45	1	0	1
5	58.65	129	9	5	0.7	0	0	2
6	148.6	206	13	3.6	0.55	1	0	4
7	60.81	233	24	6.9	1.43	1	0	1
8	90.44	150	11	4	0.79	0	0	3

name 'input1', 'input2', 'input3', 'input4', 'input5', 'input6', 'input7' respectively and the output takes the name 'output'. Input1 to input3 each is having three Gaussian membership functions and input4 to input7 each is having two Gaussian membership functions. The output has four membership functions of constant nature. The generated fuzzy expert system is then trained for the input output data deposit collected from experts. The membership functions of input1 to input 7 with their range are shown in Figure 2 to Figure 8. Fuzzy logic structure is exposed in Figure 9. The representation of rules in the neuro-fuzzy expert system is shown in Figure 10.

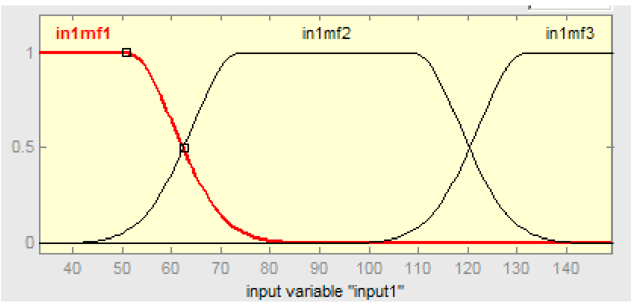

Figure 2. Membership functions for input1.

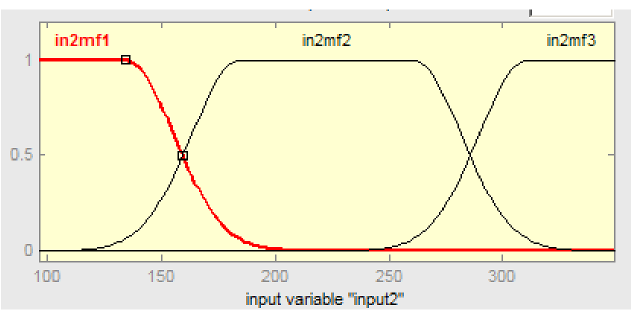

Figure 3. Membership functions for input2.

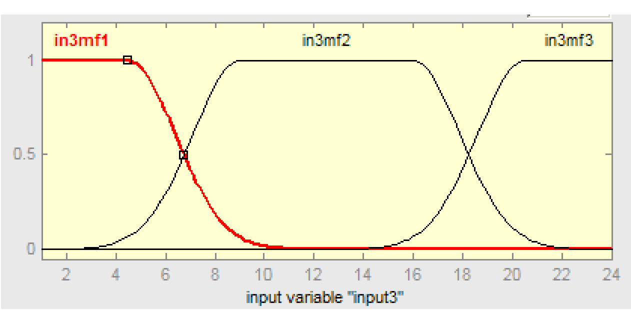

Figure 4. Membership functions for input3.

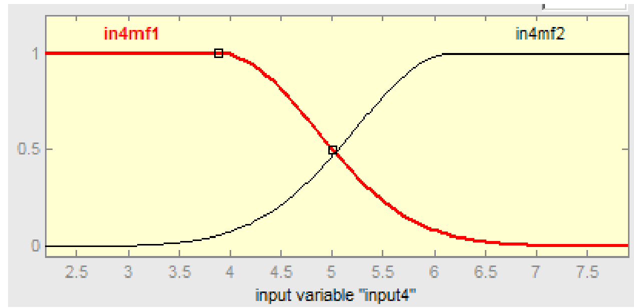

Figure 5. Membership functions for input4.

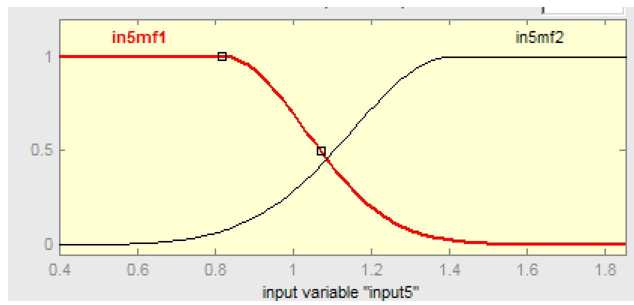

Figure 6. Membership functions for input5.

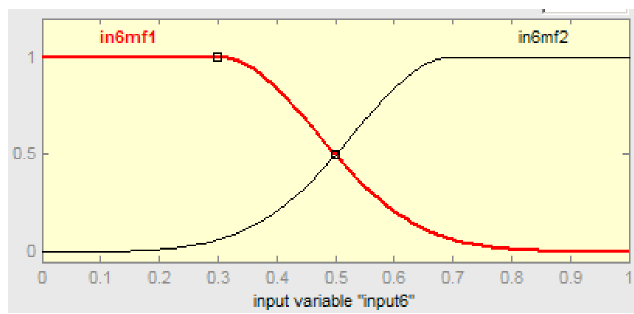

Figure 7. Membership functions for input6.

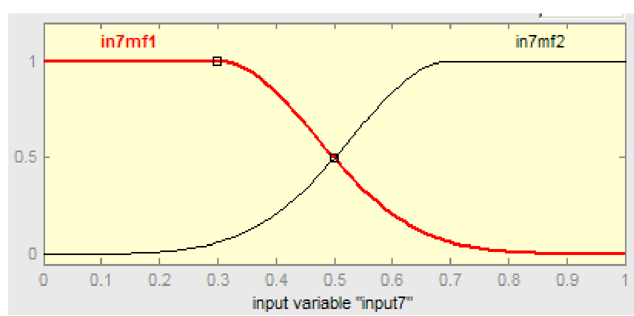

Figure 8. Membership functions for input7.

There are total 432 rules in the system. It is calculated as follow:

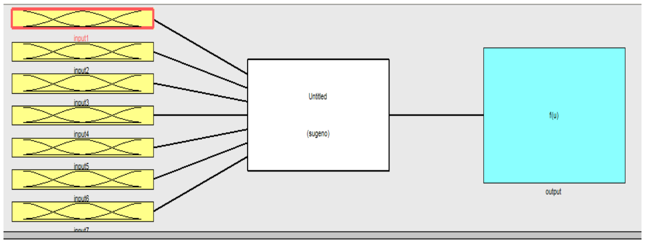

Figure 9. Fuzzy logic structure.

Total number of rules = membership functions of input1 * membership functions of input2 * membership functions of input3 * membership functions of input4 * membership functions of input5 * membership functions of input6 * membership functions of input7

Entire number of rules = 3*3*3*2*2*2*2

Entire number of rules = 432

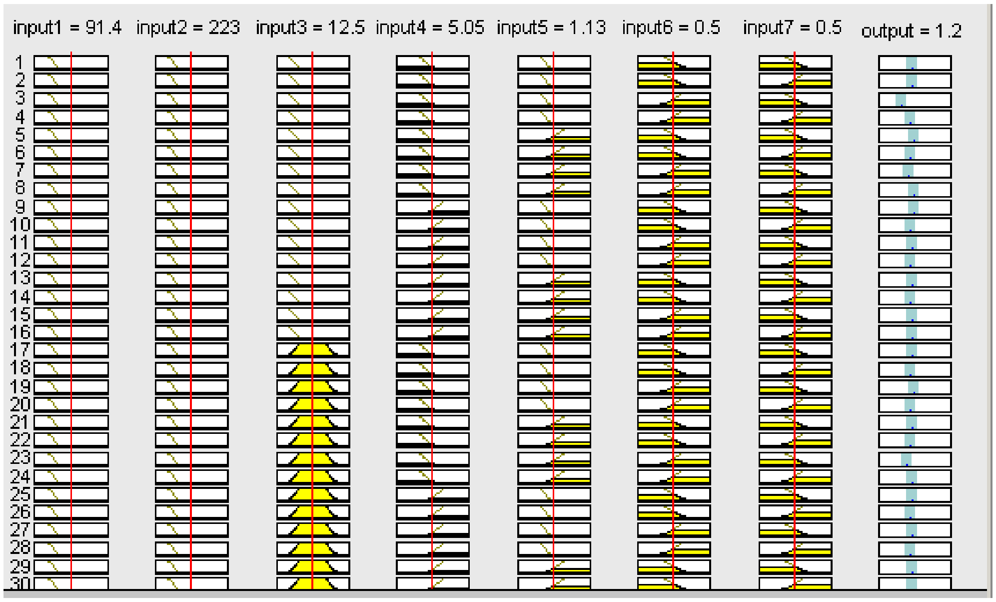

Figure 10. Rules representation in Neuro-fuzzy system.

1. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf1) (1)
2. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf2) (1)
3. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf3) (1)
4. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf4) (1)
5. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf5) (1)
6. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf6) (1)
7. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf7) (1)
8. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf8) (1)
9. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf9) (1)
10. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf10) (1)
11. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf11) (1)
12. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf12) (1)
13. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf13) (1)
14. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf14) (1)
15. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf15) (1)
16. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf16) (1)
17. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf2) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf17) (1)

Figure 11. ANFIS rules.

416. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf2) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf416) (1)
417. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf417) (1)
418. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf418) (1)
419. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf419) (1)
420. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf420) (1)
421. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf421) (1)
422. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf422) (1)
423. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf423) (1)
424. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf1) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf424) (1)
425. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf425) (1)
426. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf426) (1)
427. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf427) (1)
428. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf1) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf428) (1)
429. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf1) then (output is out1mf429) (1)
430. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf1) and (input7 is in7mf2) then (output is out1mf430) (1)
431. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf1) then (output is out1mf431) (1)
432. If (input1 is in1mf3) and (input2 is in2mf3) and (input3 is in3mf3) and (input4 is in4mf2) and (input5 is in5mf2) and (input6 is in6mf2) and (input7 is in7mf2) then (output is out1mf432) (1)

Figure 12. ANFIS rules.

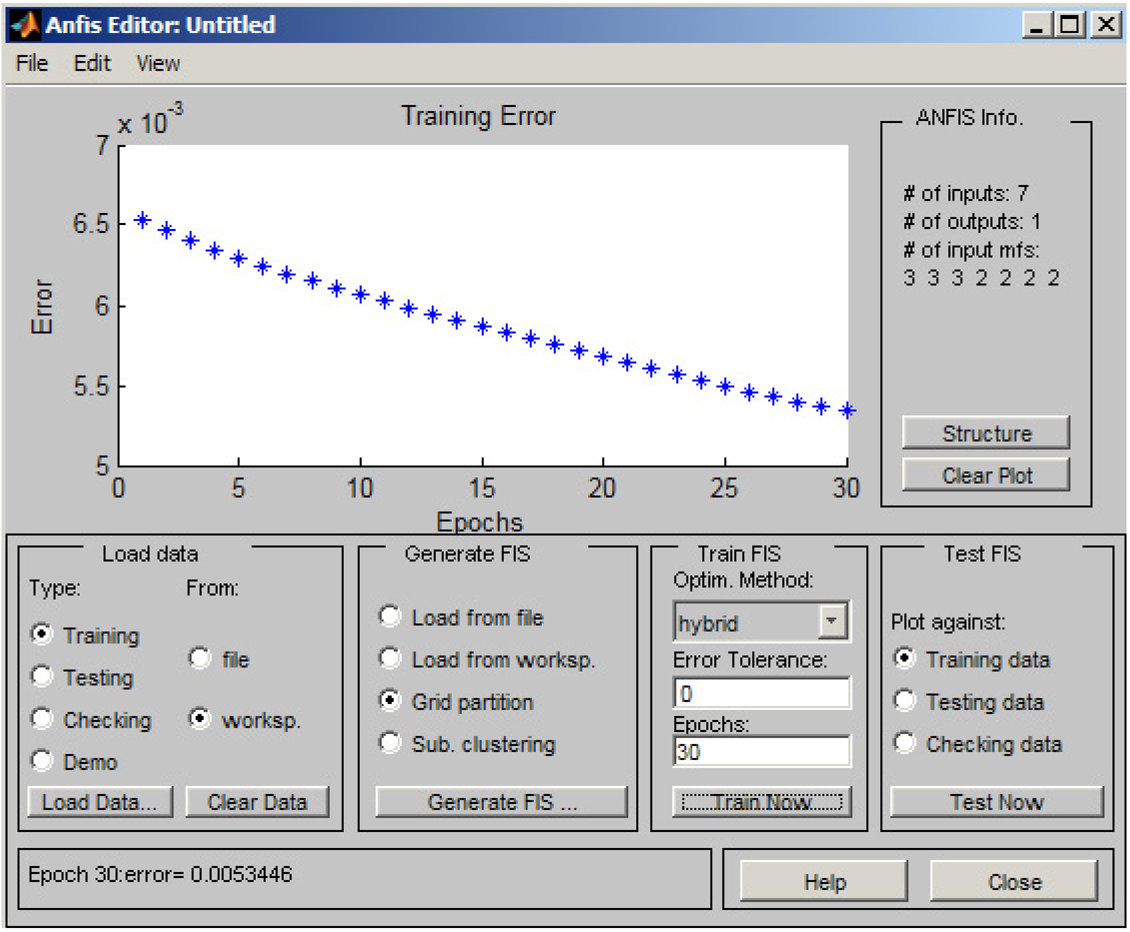

Figure 13. Training error at 30 epochs.

ANFIS rules are shown in Figure 11 and 12. Training error at 30 epochs is shown in Figure 13.

6. Results

Throughout testing the feat of the structure, the professional expert classify adequately and inadequately diagnosed patient cases by evaluating the decisions made by the system with that of the professional expert decisions made on the same patients test cases. Performance is frequently calculated by applying the figures in the matrix array. The following Table 2 illustrates the confusion matrix array for the four set classifier using neuro-fuzzy expert system.

The entries in Table 2 have the following sense in the perspective of this research:

As a result out of 80 diagnosed patients cases, in the first column, 20 diagnosed patients are sorted as severe out of which all 20 diagnosed patients are adequately sorted. The second column illustrates an idea of about 20 diagnosed patient cases, 19 are sorted as moderate and 01 patient is sorted faultily. The third column explains that out of 20 diagnosed patient cases, 18 are sorted as minor and 02 patients are sorted faultily and in the fourth column out of the 20 diagnosed patient cases, 18 are sorted as good and 02 patients are sorted faultily. On the whole out of 80 diagnosed patients' cases, 75 diagnosed patients' cases are adequately sorted and 05 diagnosed patients cases are sorted inadequately.

Number of successes = 75

Total of tests= 80

Confidence indicator = ((75/80)*100) = 93.75

The result shows that the judgments reached by adaptive neuro-fuzzy expert system are 93.75% in acceptably categorized patients and 06.25% in wrongly categorized patients. Now the severe and moderate classifiers are taken as yes. It means they are unhealthy people and minor and good classifiers are taken as no. It means they are healthy people. So the 3*3 matrix of values in table 2 is reduced to 2*2 matrixes of values which is shown in Table 3.

TP: True positive is 39
FN: False negative is 01
FP: False positive is 02
TN: True negative is 38
Sensitivity = (TP/(TP+FN)) = (39/(39+01)) = 97.5%
Specificity = (TN/(TN+FP)) = (38/(38+02)) = 95%
Precision = (TP/(TP+FP)) = (39/(39+02)) = 95.12%
Classification accuracy = ((TP+TN)/(TP+TN+FP+FN)) = ((39+38)/(39+38+02+01)) = 96.25%

Table 2. Confusion matrix array using neuro-fuzzy expert system

Severe	Moderate	Minor	Good	Class Names
20	00	00	00	Severe
00	19	01	00	Moderate
00	02	18	00	Minor
00	00	02	18	Good

Table 3. Confusion matrix with reduced dimensionality

Yes	No	Class Names
39	01	Yes
02	38	No

7. Conclusions

There are many factors associated with the nephropathy control measurement. So it is very hard for expert to reach at right decision. It is also possible that due to large number of factors, the expert can take wrong decision. This neuro-fuzzy expert system can help the expert and inexpert to measure the nephropathy control. This system is like a supporting tool that helps the expert in his prescription to keep the patient stable. This system is more accurate then the mamdani fuzzy, sugeno fuzzy and simple rule based systems. There is a need of only computer system and matlab software to implement this research work. So it may be used in hospitals. This type of system is much beneficial in developing counties like Ethiopia where the number of deaths imputed to different diseases is very high.

8. Future Scope

With the passage of time, medical study and research will identify more parameters that effect on the measurement of nephropathy control. These parameters can be incorporated into the neuro-fuzzy model being undertaken in the research work. The performance of the system can still be improved by training the neural network with different number of input output combinations.

9. References

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