Original Research Article

Diabetes Diagnosis Using Fuzzy – Neuro Hybrid Control Model

Abstract

Diabetes is caused due to an inability of a body to produce or respond to hormone insulin causing abnormal metabolism of carbohydrate which can lead to rising in sugar level in the blood. This work proposed a fuzzy - neuro hybrid control model to diagnose diabetes in terms of seven symptoms such as an increase in urination, increase in thirst, increase in fatigue, tingling in hands/ feet feet, blurred vision, sores slow to heal and significant loss of weight. 15 patients were diagnosed with sugar levels as followed 9.6mmol/l, 6.8mmol/l, 9.1mmol/l, 11.2mmol/l, 6.5mmol/l, 5.7mmol/l, 11.8mmol/l, 8.9mmol/l, 7.0mmol/l, 11.0mmol/l, 8.5mmol/l, 9.0mmol/l, 12.4mmol/l, 9.5mmol/l and 10.4mmol/l. The average diagnosis error is obtained as 0.73%, which is acceptable in medical diagnosis. In this regards, it is recommended that fuzzy- neuro hybrid control model is a good soft computing tool for diagnosing diabetes.

Keywords:-Diabetes; Soft computing; Fuzzy logic; Neural network; Suger level; Expert Domain.

1.0 Introduction

Medical diagnosis is usually not straight forward or trivial, it involves many phases. For example, when a patient complaints to a doctor of his/her health condition or symptoms. The doctor may decide to offer immediate diagnosis or further requires clinical history or ask the patient to undergo laboratory test, depending on the nature of the problem. Furthermore, based on the information gathered, the doctor may match the information in terms of previous medication taken, length of illness, treatment and response to the treatment before a final diagnosis is applied. In a note shell, the process described involves information gathering, testing, updating, validation and correction of mistakes in order to come out with the near or accurate diagnosis. In comparison, machine learning (ML) is also performed in the same manner. In machine learning, data is collected as required, trained, tested, updated, validated and errors are evaluated before final output is obtained. In addition, training and learning are involved in both cases in order to become conversant with the medical or ML scenarios. Therefore, in this regards, ML techniques are employed to diagnose diseases of interest.

In some years ago communicable diseases such as tuberculosis, human immune virus/ acquired acquire immune deficiency or syndrome (HIV/AIDS) and malaria are prominently caused of increase in mortality rate in Nigeria and Africa at large. In contrast, non-communicable diseases such as high blood pressure and diabetes have been noticed these days to increase the mortality rate in Nigeria [1 – 2]. Diabetes is a metabolic disease in which someone has high glucose in the blood usually called blood sugar. This happens, either body does not produce sufficient insulin or body cells do not respond to insulin. Diabetes is of two types (i.e, type 1 and type 2). Type 2 diabetes happens as a result of lifestyle whereby patient experiences Polydipsia (increase thirst), Polyuria (increase urination), fatigue/weakness, Polyphagia (increase hunger), Sudden vision changes, Tingling in hands/feets, Skin lesions or wound that slow to heal and significant loss of weight as symptoms. A patient suffering from this disease has a risk of developing eye problem (cataract), food complication (neuropathy or ulcers), skin complications, heart issues, hypertension (heart attack or stroke), mental health (anxiety or depression), hearing loss, gum disease, erectile disorder, wound and lesions take longer time to heal and muscles of the stomach not working properly to mention but a few. This work aims at developing fuzzy – neuro hybrid control model (FNHCM) to diagnose patient with different blood sugar levels and the following objectives shall be realized: collect a sample of blood sugar from different patients in the Hospital Laboratory, develop fuzzy – neuro model to diagnose the patient condition using the following steps. Firstly, fuzzify the sample of blood sugar collected. Secondly, prepare fuzzy rules. Thirdly, defuzzify the output. Lastly, train the deffuzified output and update its weight before comparing with the target. However, one big challenge in the area of modelling and computing is that there is a problem of inter-disciplinary cooperation, especially between medical and modelling experts. This aspect is very important because, without relevant information from the medical experts, modelling cannot be fully achieved.

Many kinds of literature have reported the use of artificial intelligence such as artificial neural network (ANN), fuzzy logic (FL), neuro-fuzzy and adaptive neuro-fuzzy inference system (ANFIS) to diagnose different diseases, which include depression [3 -5], Hypertension [6 – 8], Tuberculosis [9 -11], Malaria [12 – 14], HIV/AIDS [15] and others [16 – 17]. Diabetes is also diagnosed by different authors [18 - 20]. Soft computing tools are not restricted to the scientific application only. They are also applied in many areas of endeavours, for example, business forecasting and decision makings [21 – 26].

2.0 Method of data collection, presentation and normalization

The data is collected based on the complaints of the patients in terms of symptoms which include an increase in thirst, urination, hunger, fatigue, blurred vision, sores do not heal and significant loss of weight. Firstly, blood sample from patient is collected to test for a sugar level in the blood and the result of the test is usually obtained as follows: for, below normal blood sugar reference ranges from 0 – 3.4 mmol/l, known as hypoglycemia, normal blood sugar level, 3.5 – 6.1 mmol/l, pre-diabetic patient 6.2 – 6.9 mmol/l and diabetic patient 7.0 – 13 mmol/l. The pre-diabetes and full diabetes are called hyperglycemia. In this regards, the symptoms vector matrices shall be considered as the input ($I_i = T_i, U_i, F_i, V_{ii}, K_i, S_i, W_i$) and O_i as output vector matrix of the FNHCM (see, Figure 1), the symptoms are further normalized as given in Table 1 and sample of the blood sugar collected is presented in Figure 2

Table 1 Symptoms and abbreviations

S/N	Symptoms	Abbreviations
1	Polyuria (increase urination)	*U*
2	Polydipsia (increase thirst)	*T*
3	fatigue/weakness	*F*
4	Sudden vision changes	*V*

5	Tingling in hands/feets	K
6	Wound that slow to heal	S
7	Significant loss of weight	W
8	High normal blood sugar	h_0
9	High blood sugar	h_1
10	Very high blood sugar	h_2
11	Very very high blood sugar	h_3
12	Sugar level/Patient condition (FLC)	O_i
13	Hypoglycemia	xO_i
14	Glycemia	*you*
15	Hyperglycemia	zO_i
16	Patient condition (Fuzzy – neuro)	O_{i-n}

This paper integrates two different artificial intelligent techniques in order to diagnose the blood sugar level. (i.e, fuzzy logic controller (FLC) and artificial neural network (ANN) known as FNHCM as depicted in Figure 1.

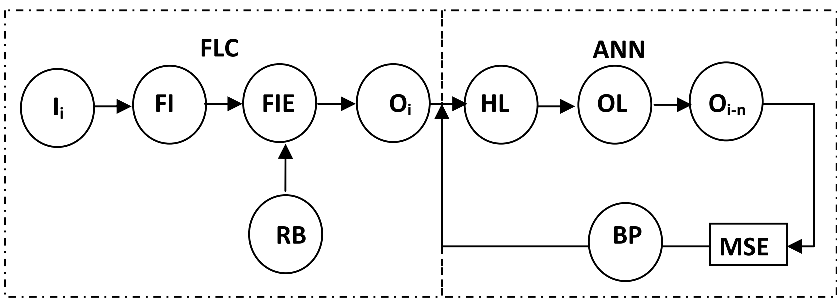

Figure 1 Fuzzy – neuro hybrid control model

Where I_i = input vector matrix, FI = fuzzified input, FIE = fuzzy inference engine, RB = rule base, HL = hidden layer, OL = output layer, O_i = fuzzy output, MSE = mean square error (e), BP = back propagation and O_{i-n} = fuzzy – neuro output.

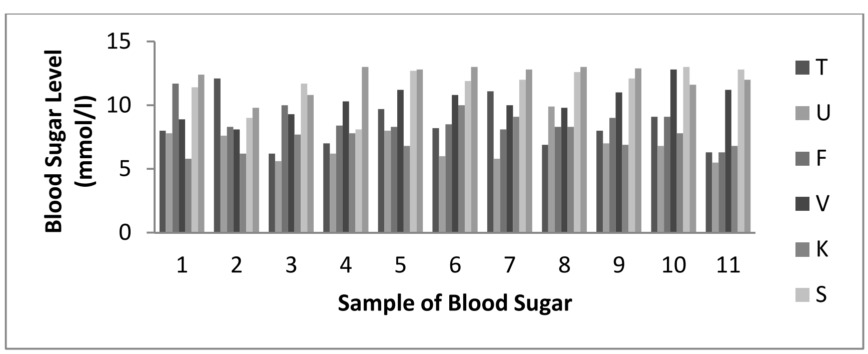

Figure 2 Sample of blood sugar collected

2.1 Implementation of the fuzzy – neuro hybrid model

Before implementing of the FNHCM, the following algorithms need to be followed using the flow chart in Figure 3.

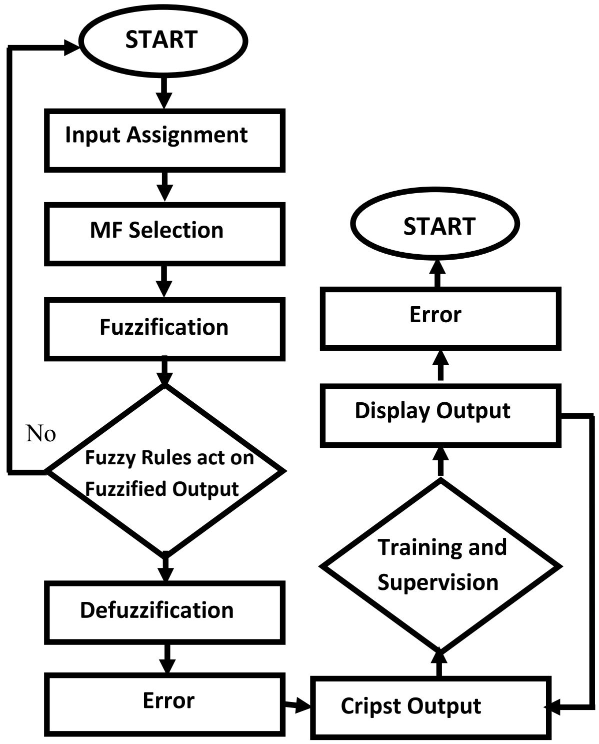

Figure 3 Fuzzy – neuro algorithm flow chart

Usually, the input/output vector matrices are fuzzified based on the range of the data collected, from minimum to the maximum. Such that, T = 6.2 – 11.0 mmol/l, U = 5.5 – 10.0 mmol/l, F = 8.0 – 13 mmol/l, V = 8..1 – 12.8 mmol/l, K = 5.8 – 9.9 mmol/l, S = 9.50 – 13.0 mmol/l, W = 9.0 – 13.0 mmol/l and O_i = 1.00 – 13.0 mmol/l which corresponds to the symptoms/patient condition classified into linguistic terms as $T, U, F, V_i, K, S, W, O_i$ and each item is classified in terms of sugar levels as ‘U’, (h_0U) 5.5 – 6.1 mmol/l, (h_1U) = 6.2 – 7.0 mmol/l, ($h_3 U$)=*7.1 -10.0mmol/l*, ‘T’, (h_1T) = 6.2 – 7.0 mmol/l, ($h_2 T$) = 7.1 – 9.9 mmol/l , (h_3T) = 10.0 – 13.0 mmol/l , ‘F’, ($h_2 F$) = *8.0 – 9.9 mmol/l*, (h_3F) = 10.0 – 13.0 mmol/l, ‘V’, ($h_2 V$) = 8.0 – 9.9 mmol/l, ($h_3 V$) = 10.0 – 12.8 mmol/l, ‘K’, (h_0K) = 5.8 – 6.1 mmol/l, (h_1K) = 6.2 – 7.0, (h_2K) = 7.1 – 9.8 mmol/l, ‘S’, (h_2S), (h_3S), ‘W’, (h_2W) = 9.5 – 9.9 mmol/l, (h_3W) = 10 – 13 mmol/l, ‘O’, (xO_i) = 0.5 – 3.1 mmol/l, (y_nO_i) = 3.5 – 6.1 mmol/l (zO_i) = 6.2 – 13.0 mmol/l. The information given above for one symptom (thirst) is mapped into a triangular membership function (TMF) as given in Eq. 1 and further illustrated in Figure 3

$$f(T; a, b, c) = \begin{bmatrix} 0, & T \leq a \\ \frac{T-a}{b-a}, & a \leq T \leq b \\ \frac{c-T}{c-b}, & b \leq T \leq c \\ 0, & c \leq T \end{bmatrix} \qquad (1)$$

where b locates the height and a, c locate the base of the TMF [3].

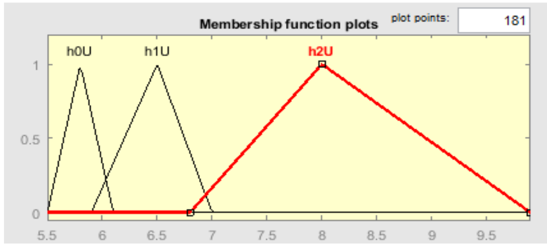

Figure 4a Increase in urination MF

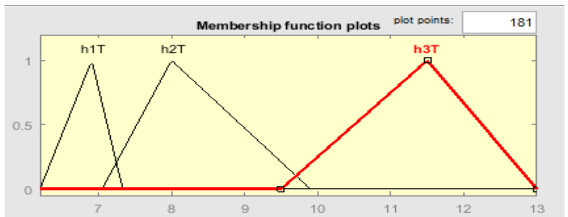

Figure 4b Increase in thirst MF

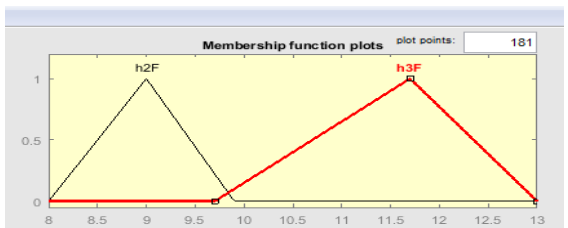

Figure 4c Increase in fatigue

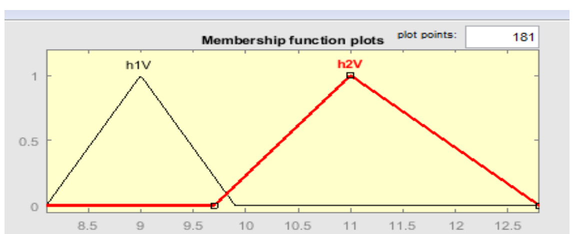

Figure 4d Blurred Vision MF

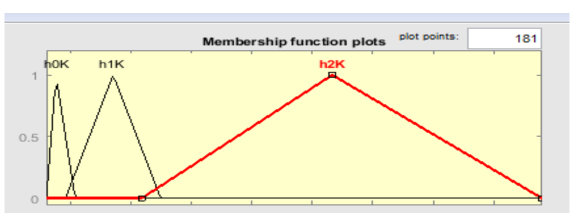

Figure 4e Tingling in hands/feets MF

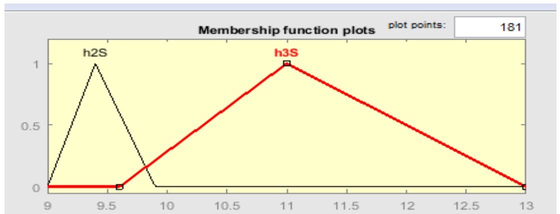

Figure 4f Sores that are slow to heal MF

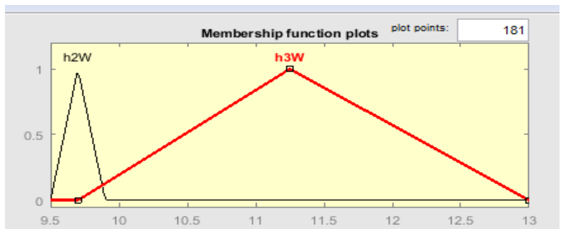

Figure 4g significant weight loss MF

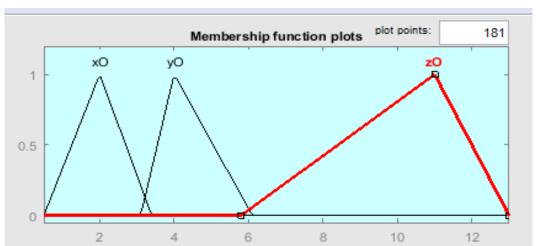

Figure 4h Patient condition MF

Furthermore, few fuzzy rules are then formulated based on the information taking from the team of experts (i.e, group of experienced Laboratory Technologies and Medical Doctors) in respect to the symptoms/patient conditions such that, *if U is* h_0U *and T is* h_1T *then* O_i *is* yO_i, *if V is* h_1V *and W is* h_2W *then* O_i *is* zO_i, and the remaining 126 rules are formed in a similar manner. These rules use firing strength (ϕ) to act on the fuzzified output in the fuzzy inference engine (FIE) in AND operation mode as given in Eqs. 2 – 3

$$\phi = \min\left(\mu_U(O_i), \mu_T(O_i)\right) \quad (2)$$

$$\phi = \min\left(\mu_V(O_i), \mu_W(O_i)\right) \quad (3)$$

And the output of FIE is defuzzified using Eq. 4.

$$f(O_i) = \frac{\sum_{i=1}^{n} O_i \mu_{O_i}(O_i)}{\sum_{i=1}^{n} \mu_{O_i}(O_i)} \quad (4)$$

The defuzzified output O_i becomes the input of the ANN (see, Figure 1). The input layers of the ANN are used to amplify the defuzzified output, presents it to the network. In addition, it has neither connecting weights nor activation functions. The network is trained and the HL, receives the amplified fuzzy output O_i (i = 1, 2, ..., n), connect it to the neurons N_j (j =1, 2, ...n) and compute it using Eq. 5.

$$h_j = f\left(\sum_{i=1}^{n} w_{ij} O_i\right) + bw_{0i} \quad (5)$$

$$\text{where } f = \frac{1}{1+e^{-hj}} \qquad (6)$$

f is the log-sigmoid activation function of the hidden layer outputs. The outputs of the hidden layer is then multiple by their connecting weights (w) plus the bias and the weights are computed using Eq. 7

$$O_{h-1} = \left(\sum_{i=1}^{n} h_i w_i\right) + b_{03} \qquad (7)$$

Therefore, output of the fuzzy – neuro control model *(O_{i-n})* is obtained using Eq. 8

$$O_{i-n} = f_0 O_h \qquad (8)$$

f_0 is the linear transfer function. $O_i = (xO/yO/zO)$ is compared with the target to give O_{i-n} and the error connection learning rule base after the first stage of the training is obtained using Eq. 9

$$e = 1/2(t\arg et - O_{i-n})^2 \quad (9)$$

If the error obtained after first training is not within the acceptable range of medical diagnosis, the weights are then back propagated by training the network several times until minimum acceptable error range is achieved as summarized in Table 2. The weights update between the output and hidden layer are performed using Eqs. 10 – 11.

$$\Delta w_1 = \beta \times e \times h_1 \qquad (10)$$

$$\Delta w_2 = w_1 + \Delta w_1 + (\alpha \times \Delta(d-1)) \quad (11)$$

where α and β are momentum and learning rate respectively. Δ (d – 1) is the value of previous delta change of the weight w_1 and the overall performance of the fuzzy – neuro hybrid control model can be measured by its average accuracy (S_m), given in Eq. 12

$$S_m = \frac{O_{i-n}}{I_i} \times 100\% \qquad (12)$$

3.0 Result and discussion

Figure 4(a-h) show the TMF of the symptoms and the patient conditions, increase in urination, increase in thirst, tingling in hands or feet, are represented by three membership functions, increase in fatigue, blurred vision, sores slow to heal and significant weight loss are presented by two membership function. These are formulated based on the data collected. However, 84 sample of blood is collected from different patients as depicted in Figure 2. In this work, two training techniques were performed that is, in fuzzy logic control and artificial neural network domains. The FLC training is performed offline with the fuzzified inputs and sets of rules 2^7 *(128)* using firing strength in FIE as stated in section (2.1), and produced defuzzified output shown in Figure 5.

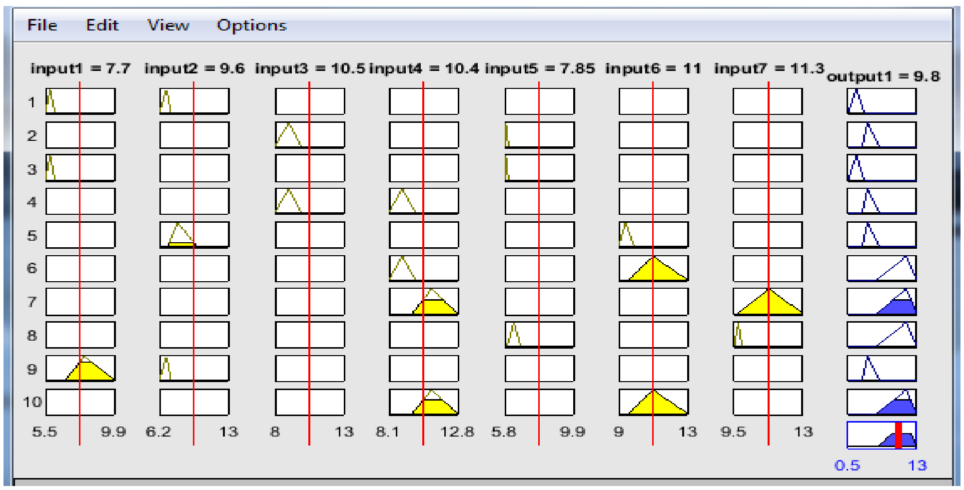

Figure 5 FLC rule viewer

Figure 5, depicts FLC model output usually called the rule viewer, the yellow colours indicate the symptoms and the blue colour presents the patient condition or the diagnosis. This is obtained when two or more symptoms are matched together. See, for instance, an example of one case, it can be seen on the rule view that, the patient condition is diagnosed as 9.8mmol/l and it corresponds to hyperglycemia (diabetic) and other cases can be obtained in the same manner as summarized in Table 2. Furthermore, the output of FLC is forwarded into the input of an ANN where the FLC output is trained, test and validated to minimize the likely error obtained at the output of the FLC as also summarized in Table 2. During the training, 70% of the values are allocated for training, 15% for testing and 15% for validation. The network was trained several times through back propagation algorithm and weights are updated until minimum acceptable error or desired output is obtained.

Table 2 Patient diagnosis

Cases	FLC Output (O_i)	FNHCM Output ($O_{i\text{-}n}$)	Error (e)	Diagnosis
1	9.8	9.6	- 0.2	Diabetic
2	6.8	6.8	0.0	Pre – diabetes
3	9.9	9.1	-0.8	Diabetic
4	11.0	11.2	+0.2	Diabetic

5	7.0	6.5	-0.5	Pre – diabetes
6	12.4	11.9	-0.5	Diabetic
7	6.0	5.7	-0.3	Negative
8	8.4	8.9	+0.5	Diabetic
9	7.6	7.4	-0.2	Pre – diabetic
10	10.6	11.0	+0.4	Diabetic
11	8.8	8.5	-0.3	Diabetic
12	10.0	9.0	-1.0	Diabetic
13	12.3	12.4	+0.1	Diabetic
14	9.0	9.5	+0.5	Diabetic
15	10.7	10.4	-0.3	Diabetes
∑Error	**140.5**	**137.9**	**0.73**	
Ave. Error	**9.37**	**9.19**		

From Table 2, 15 patients were diagnosed, where 11 patients, 3 patients and 1 patient are diagnosed diabetic, pre-diabetic and only one person is negative respectively. These 15 patients were selected at random in order to test for the model performance. Figure 6 depicts the error analysis, the positive and the negative bars present the difference between the FLC and FNCM outputs, the five positive bars indicate where FNCM output error is higher while the ten negative bars indicate where FLC error is higher. In comparison, FLC output has a higher error than FNCM output by 2.6, and the FLC error is minimized to 0.73 by the FNHCM. However, the accuracy of the fuzzy – neuro model is computed as 99.27% from Eq. 12. In this work, diagnosis error is minimized compared to what is obtained by [27 - 30]

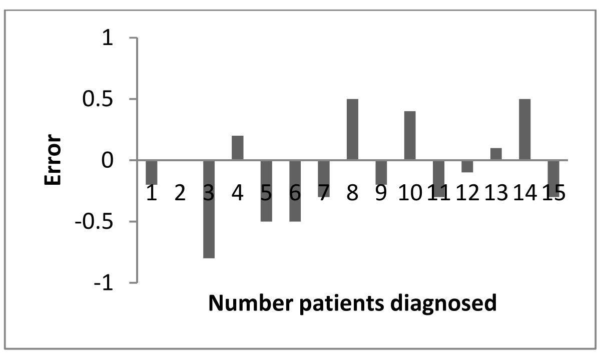

Figure 6 Error analysis

Figure 7, compares the FLC and fuzzy – neuro output. It is observed that fuzzy – neuro output is better than FLC output. This is because fuzzy – neuro has less prediction error as also presented by [31 - 33].

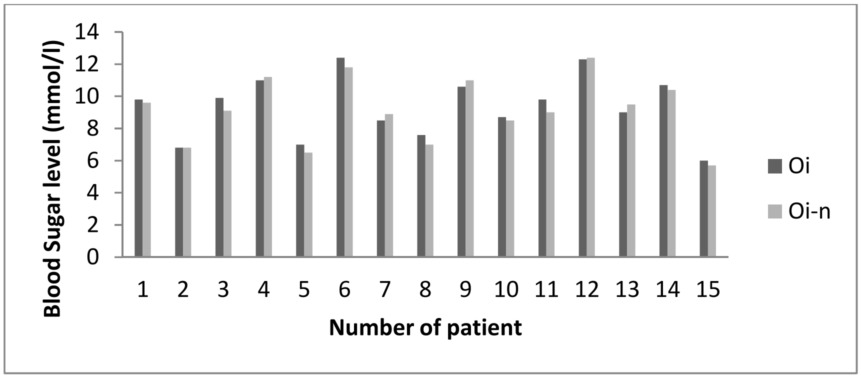

Figure 7 FLC vs Fuzzy – neuro output

4.0 Conclusion

In this work, fuzzy – neuro was developed to diagnose patient with blood sugar. Out of the 84 samples of blood sugar levels collected. 15 patients were selected at random and diagnosed, it is noticed that 11 patients, 4 patients and one person were diagnosed with diabetes, pre-diabetes and negative respectively. The average error obtained is 0.73 which is acceptable in medical diagnosis and accuracy of the model is obtained as 99.27%.

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