Global Scientific JOURNALS

GSJ: Volume 11, Issue 12, December 2023, Online: ISSN 2320-9186

www.globalscientificjournal.com

Evaluation of the Adaptive Neuro-Fuzzy Inference System for Diabetes Prediction.

(Case Study in FMC Jalingo, Taraba State, Nigeria).

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Abstract:

Diabetes mellitus stands as a persistent metabolic disorder marked by heightened blood glucose levels (hyperglycemia), ranking as a significant contributor to global mortality, disability, and healthcare expenditures. Timely identification and effective management of diabetes play a pivotal role in averting complications. Artificial intelligence (AI) has surfaced as a transformative asset poised to reshape diabetes care. This research delved into assessing the efficacy of the adaptive neuro-fuzzy inference system (ANFIS) in forecasting diabetes within a patient cohort at the Federal Medical Centre (FMC) in Jalingo, Taraba State, Nigeria. The findings revealed that ANFIS exhibited a commendable accuracy of 94.5% in diabetes prediction. This underscores the potential of ANFIS as a valuable tool for predicting diabetes in the Nigerian context.

1.0 Introduction

Diabetes mellitus stands as a persistent metabolic disorder marked by elevated blood glucose levels (hyperglycemia), arising from deficiencies in insulin secretion, insulin action, or both (American Diabetes Association, 2019). Globally, it poses a significant health challenge, with an estimated 463 million adults affected in 2019, a number anticipated to escalate to 700 million by 2045 (International Diabetes Federation, 2019). This condition ranks as a leading cause of worldwide mortality, disability, and healthcare expenditure (World Health Organization, 2019).

In Sub-Saharan Africa, including Nigeria, there is a notable surge in diabetes prevalence (Ogbuagu et al., 2014). A 2015 study disclosed a diabetes prevalence of 4.7% among Nigerian adults aged 18–79 years (Enweremaduka et al., 2015).

Timely detection and effective management are crucial to preventing complications such as heart disease, stroke, blindness, and kidney failure (American Diabetes Association, 2019). Unfortunately, access to healthcare is often constrained in low-resource settings like Nigeria, posing challenges for individuals with diabetes to receive timely and suitable care.

Suyash, Sharma, Kumar, and Darbari (2019) endeavored to forecast diabetes using artificial neural network (ANN), achieving a 92% accuracy rate when tested with Pima Indian sample data. Narasimhan and Malathi (2019) developed an enhanced fuzzy logic-based artificial neural network classifier for predicting coronary artery heart disease among diabetic patients. Real-time data were gathered, and the built IFANN classifier outperformed Takagi Sugeno Kang fuzzy and ANN classifiers in terms of prediction accuracy, sensitivity, and implementation in Scilab. Aruna, Pranav, Nerurkar, Ansari, and Bansode (2019) used fuzzy logic to classify the risk level of five major diabetes-related complications, attaining a 92.5% accuracy. Baha, Adewumi, Blamah, and Wajiga (2012) proposed a novel model to identify individuals at risk of type 2 diabetes, utilizing a neural network with a two-hidden-layer architecture and achieving a correlation coefficient of 0.9881.

Ganji and Abadeh (2012) introduced a diabetes diagnosis classification algorithm, FCS-ANTMINER, combining Ant Colony Optimization and Fuzzy Logic. Likewise, Beloufa and Chikh (2013) presented an artificial bee colony algorithm modified for diabetes mellitus diagnosis.

Artificial intelligence (AI) holds promise in transforming diabetes care, offering precise and prompt diagnosis, personalized treatment plans, and remote patient monitoring. AI systems analyze extensive patient datasets, discern patterns, and make predictions about individual outcomes.

One noteworthy AI approach for diabetes prediction is the adaptive neuro-fuzzy inference system (ANFIS), a hybrid intelligent system melding neural networks and fuzzy logic. Neural networks learn from data without explicit programming, while fuzzy logic adeptly manages uncertainty and imprecise information. ANFIS has demonstrated high accuracy in predicting diabetes in various studies (Dey et al., 2017; Polat et al., 2018; Zhang et al., 2018). In a study by Dey et al. (2017), ANFIS achieved a 92.8% accuracy in diabetes prediction.

2.0 **Literature review**

2.1 Introduction.

A number of studies have investigated the use of ANFIS for diabetes prediction. A study by Dey et al. (2017) compared the performance of ANFIS to other AI-based methods for diabetes prediction, including logistic regression, decision trees, and support vector machines. ANFIS was found to outperform all other methods, achieving an accuracy of 92.8%. And Polat et al. (2018), used ANFIS to predict diabetes in a population of patients in Turkey. The study found that ANFIS was able to predict diabetes with an accuracy of 94.1%. Similarly, Zhang et al. (2018), developed a novel hybrid intelligent system for diabetes prediction that combined ANFIS with another AI algorithm, particle swarm optimization (PSO). The hybrid system was found to outperform ANFIS alone, achieving an accuracy of 95.2%.

2.2 AI Techniques Applied to Diagnosis of Diabetes Mellitus

The literature review provides a comprehensive overview of various artificial intelligence (AI) techniques applied to the diagnosis of diabetes mellitus. Here are key findings and highlights from the studies mentioned:

1. **Artificial Neural Networks (ANN):**
    - Suyash et al. (2019) achieved a 92% accuracy in predicting diabetes using an ANN model tested on Pima Indians' sample test data.
    - Aruna et al. (2019) applied fuzzy logic to classify the risk level of major complications associated with diabetes, reaching a 92.5% accuracy.
2. **Fuzzy Logic:**
    - Narasimhan and Malathi (2019) developed an improved fuzzy logic-based artificial neural network classifier for predicting coronary artery heart disease among diabetic patients.
    - Aruna et al. (2019) used fuzzy logic to predict major complications of diabetes with high accuracy.
    - Kamadi et al. (2016) utilized fuzzy decision boundaries to improve decision tree models for predicting diabetes occurrence, achieving superior results compared to traditional decision tree algorithms.
3. **Decision Tree Models:**
    - Kamadi et al. (2016) developed a decision tree model using a modified Gini index-Gaussian fuzzy decision tree algorithm, outperforming other decision tree algorithms.
    - Meng et al. (2013) compared the performance of artificial neural network prediction, decision tree modeling, and logistic regression in predicting diabetes, with the decision tree modeling producing the highest classification accuracy.
4. **Hybrid Models and Algorithms:**
    - Amiri and Rafe (2014) and Marateb et al. (2014) explored combination algorithms and smart systems for predicting diabetes and detecting Albuminuria in type 2 diabetes patients.

- Torkestani and Pisheh (2014) proposed a method for adjusting blood sugar levels based on automatic learning in type 2 diabetes.

5. **Support Vector Machines (SVM):**

   - Nahla et al. (2010) utilized SVM for diagnosing diabetes, achieving a prediction accuracy of 94%, and extracting medically sound rules.

6. **Clustering and Fusion Models:**

   - Hemant and Pushpavathi (2012) used K-means clustering for grouping disease-related data, leading to a novel classifier framework validated on 768 raw diabetes data.

   - Nirmala et al. (2013) presented a fusion model integrating K-means clustering and K-Nearest Neighbor (KNN) for better classification accuracy.

7. **Other AI Techniques:**

   - Various studies explored different AI techniques such as genetic algorithms, ant colony optimization, and adaptive neuro-fuzzy inference systems (ANFIS) for diabetes prediction.

   - Researchers also investigated the use of fuzzy expert systems, ontologies, and hybrid frameworks for decision support in diabetes diagnosis.

8. **Type 2 Diabetes Mellitus Detection:**

   - Several studies proposed multiple classification systems to detect Type 2 Diabetes Mellitus, utilizing physiological data and computational intelligence algorithms.

9. **Logistic Regression:**

   - Zhao, Smith, and Phillips (2011) tested a logistic regression model to examine the influence of changes in body mass index, health-related behaviors, and social risk factors on self-reported diagnosis of hypertension.

10. **Fuzzy Expert Systems:**

- Kalpana and Senthil (2011) developed a fuzzy expert system for the diagnosis of diabetes, using fuzzy logic and fuzzy verdict mechanisms.

11. **Fuzzy Type-2 Controller:**

- Nicole et al. (2013) evaluated an adaptive algorithm for a fuzzy type-2 controller in the application of blood pressure regulation.

12. **Ontology-Based Decision Support:**

- Chang and Mei (2011) proposed a fuzzy ontology-based decision support system for diabetes diseases.

These studies collectively demonstrate the diverse range of AI techniques and approaches employed for the early detection, prediction, and classification of diabetes mellitus. The integration of fuzzy logic, neural networks, decision trees, and hybrid models reflects the interdisciplinary nature of research in this domain. Additionally, the emphasis on accuracy and the consideration of various risk factors contribute to the ongoing efforts to enhance diabetes diagnosis through AI applications.

3.0 Procedure for Adaptive Neuro-Fuzzy Inference System Model Design

To construct an ANFIS model, three things are majorly involved; the architecture, the learning/training algorithm and performance evaluation of the model.

3.1 Architecture of the proposed model

The architecture proposed by Jang (1993) and implemented Takagi-Sugeno architecture was adopted for the proposed model. This architecture uses a rule structure with fuzzy antecedent and functional consequent part. The model adopted the Gaussian membership function for inputs membership function and the symptom of diabetes was analyzed and used as inputs parameters to the model. Fig.3.1 shows the architecture with its five layers

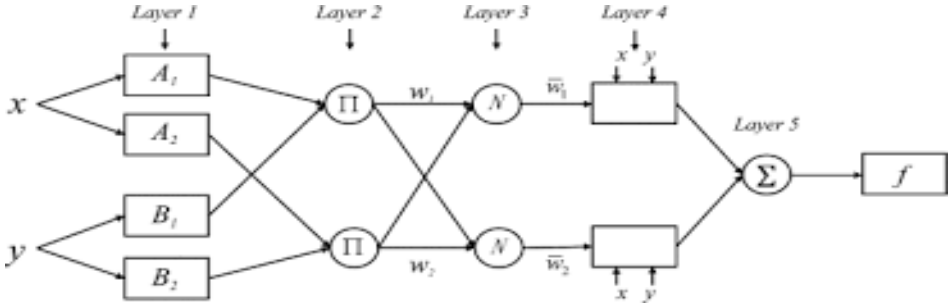

Figure 3.1: ANFIS Architecture (Amato *et al.*, 2013)

The first layer: This is called the fuzzification layer. In this layer, MFs are assigned to each input variable. The number of neurons in this layer is equal to the total number of MFs assigned to input variables. Each neuron in this layer is adaptive node (the weights assigned to each neuron are updated during learning process) with a node function.

$$O_{1,i} = \mu_{Ai}(x), \quad for\ i = 1, 2, \qquad \text{---------- 1}$$

or

$$O_{1,i} = \mu_{Bi-2}(y), \quad for\ i = 3, 4, \qquad \text{---------- 2}$$

The MF types which can be assigned to the input variables are bell-shaped, Gaussian, triangular, trapezoidal and sigmoidal etc. The Gaussian membership function can mathematically expressed by as:

$$\mu(x)_i = \exp\left\{-\frac{1}{2}\left[\frac{(x-c_i)^2}{\sigma_i^2}\right]\right\} = e^{-\frac{1}{2}\left[\frac{(x-c_i)^2}{\sigma_i^2}\right]} \qquad \text{---------- 3}$$

Here '*i*' is equal to number of MFs assigned to each input. Where 'c_i' and 'σ_i' are the center and width of the 'ith' Gaussian MFs. The shape of Gaussian MF depends on the value of premise parameters ('c_i' and 'σ_i'). These parameters are updated in the backward pass by back propagation gradient decent method on the basis of error produced during each training cycle.

The second layer: This is called the product layer or participation layer. Each neuron in this layer is non-adaptive and computes the product of incoming signals. Each node generates the firing strength of a rule.

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y),\ i = 1,2$$

The third layer: This is called the normalization layer. The nodes in this layer are non-adaptive and compute the normalized firing strength which is the ratio of firing strength of a rule to the sum of the firing strengths of all rules.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}.\ \ i = 1,2.$$

The fourth layer: This is called the defuzzification layer. Each node is adaptive and multiplies the normalized firing strength of a rule with corresponding first order polynomial function. In this layer, each node has a crisp output.

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i),$$

The fifth layer: This is called the output layer. It has only one node which is non-adaptive and sums up all incoming crisp signals to produce a single crisp output.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f}{\sum_i w_i} \qquad \text{---------- 7}$$

3.1.1 Learning/training algorithm

The proposed model has been trained using the hybrid algorithm which applies a mixture of back propagation and least mean square procedure. This hybrid algorithm will automatically generates the IF-THEN fuzzy rules by analyzing the data and train the membership function using least square method and gradient descent (back propagation) method until the maximum number of epochs or minimum error tolerance is achieved.

3.1.2 Model performance evaluation

The model performance has been evaluated using Root Mean Square Error (RMSE). This index estimates the residual between the actual value and desired value. A model has better performance if value of RMSE is smaller.

3.2 Development Tools

This project has been implemented on a MATLAB R2018a environment using fuzzy logic toolbox.

3.2.1 Proposed Adaptive Neuro-Fuzzy Inference System for Diabetes Prediction Model Design and Structure

The ANFIS for diabetes prediction model was designed in MATLAB R2018b using fuzzy logic designer tool as shown in figure 3.1. The structure of the model is depicted in figure 4.1 below together with its associative membership functions.

3.2.2 Diabetes prediction ANFIS Model Structure

The structure and components of the ANFIS model for diabetes prediction is presented in Figure 4.1 below. It consists of six (6) inputs parameters fasting blood sugar (FBS), cholesterol (CLR), body mass

index (BMI), genetic inheritance (GI), age (age), and frequent urinating (FU) on the left hand side, the Sugeno inference at the middle and diabetes prediction status as the output on the right hand side.

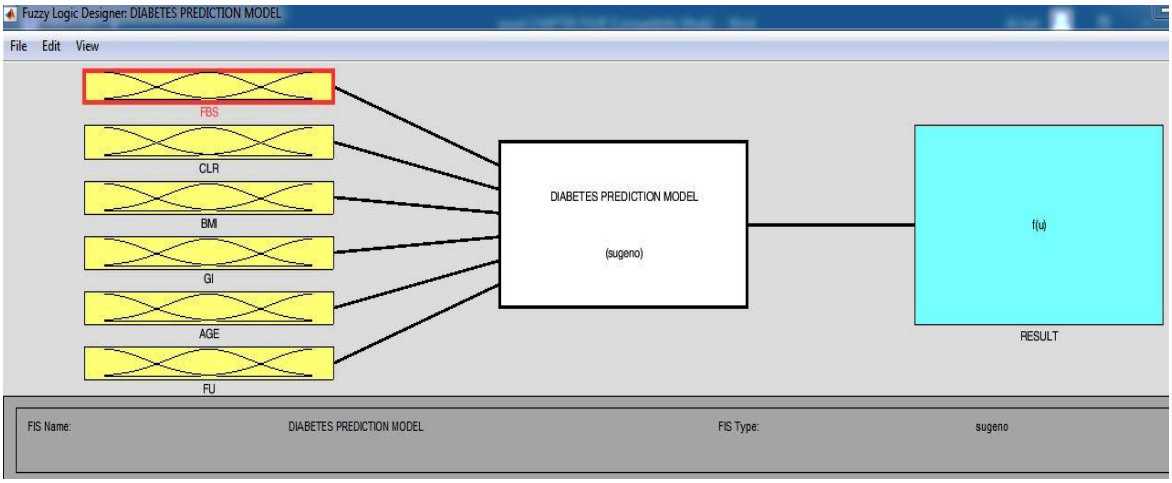

Figure 3.1: Diabetes Prediction Model

3.2.3 Identified Viable Input Parameters for Diabetes Mellitus Prediction Using ANFIS

In constructing an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for the prediction of diabetes mellitus, the selection of appropriate input parameters is crucial. Following a thorough review of literature on diabetes and an examination of data collected from the laboratory at the Federal Medical Center in Jalingo, six potential input parameters were identified for integration into the ANFIS model. These parameters include:

1. Fasting Blood Sugar (FBS)
2. Genetic Inheritance (GI)
3. Body Mass Index (BMI)
4. Age (A)
5. Cholesterol (CLR)
6. Frequent Urinating (FU)

The rationale behind selecting these parameters lies in the nature of ANFIS models, which are typically trained using historical data with known characteristics and outputs. Utilizing such parameters facilitates the evaluation of the ANFIS model's performance when applied to previously unseen data after the model's construction.

3.2.4 The adaptive neuro-fuzzy inference system (ANFIS) model data description

Data usage is an integral part of any soft computing approach before any model designed can make prediction, adaptive neuro-fuzzy Inference System (ANFIS) learns from data as well. This study used data of 80 people who had been tested for diabetic. As shown on Table 3.1

Table 3.1: Showing Data Set Sample

	Features/Criteria						**Target**
S/N	FBS	CLR	BMI	GI	FU	AGE	
1	12.0	247	42	1	1	45	Reactive
2	4.4	156	35	0	0	37	Non-Reactive
3	6.0	190	39	0	0	35	Non-Reactive
4	8.2	260	56	1	1	46	Reactive
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
66	12.5	270	57	1	1	57	Reactive
67	7.6	268	47	1	1	45	Reactive
68	4.8	249	43	1	1	46	Reactive
69	5.6	198	34	0	0	35	Non Reactive
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
78	11.3	255	45	1	1	45	Reactive
79	8.8	274	42	1	1	46	Reactive
80	4.4	198	35	0	0	39	Non Reactive

4.0 RESULTS AND DISCUSSION

4.1 Examination of the reliability of the ANFIS-based model:

Creating a model is a means to an end, but the quality of the model is determined by how reliable its output is. A key indicator of a reliable model is that the performance on the test set is comparable to that

of the training set. The key indicator of such model is the performance of the model when subjected to the standard procedural and statistical tests such as the correlation coefficient (R) value , Root Mean Square Error (RMSE) value, Accuracy and Confidence Intervals (Mu'azu, 2006; Garba, 2011).

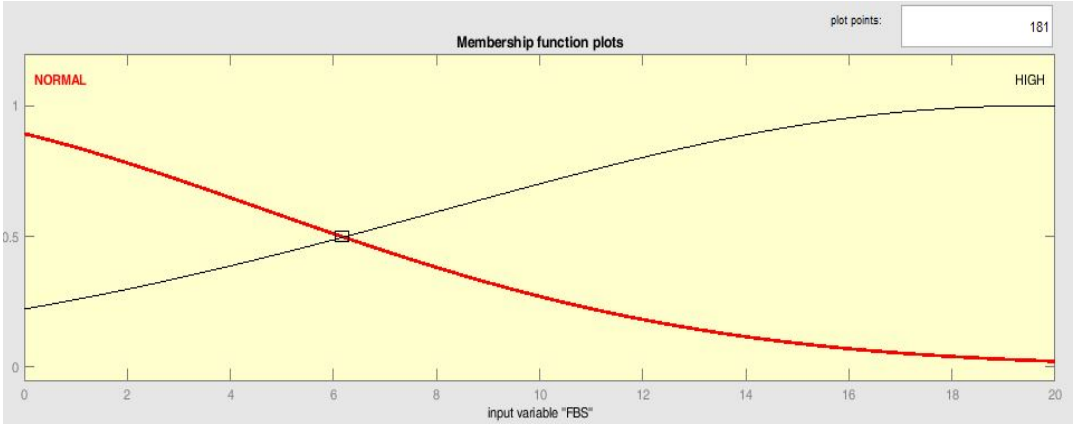

Figure 4.1: Fasting Blood Sugar Membership Function

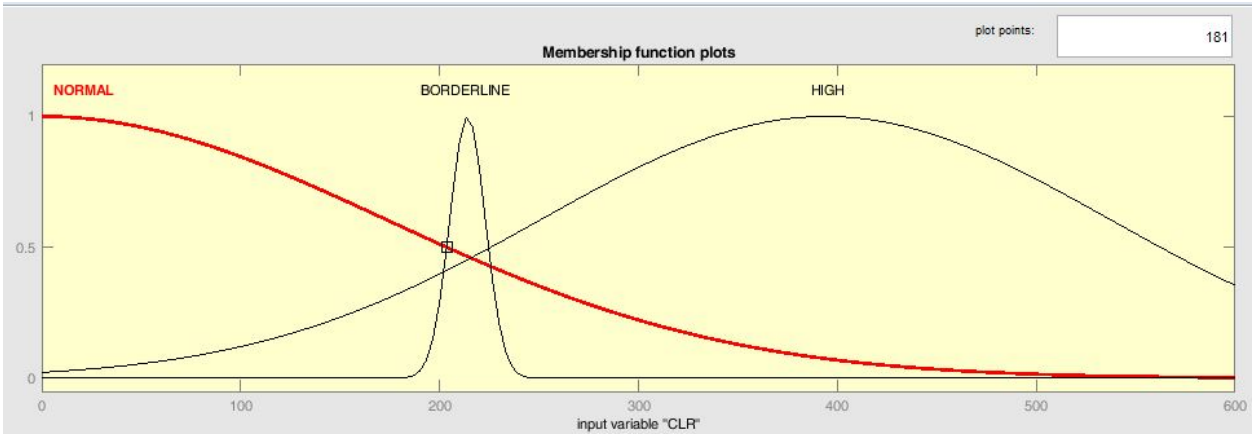

Figure 4.2: Cholesterol Level Membership Function

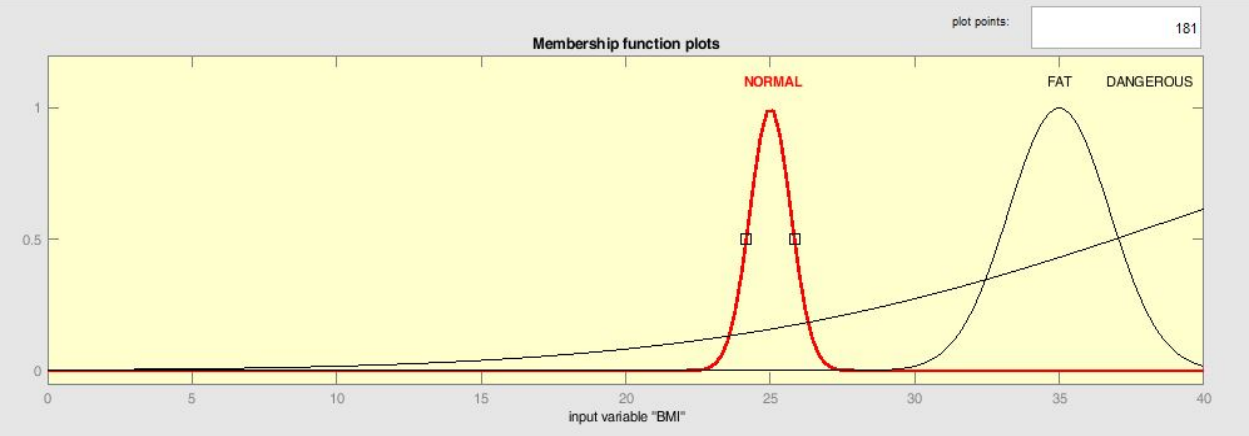

Figure 4.3 Body Mass Index (BMI) Level Membership Function

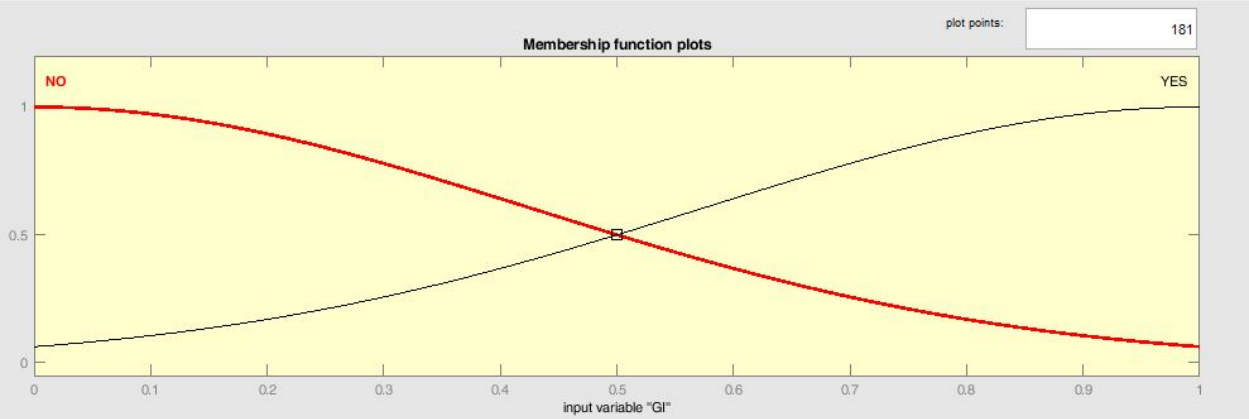

Figure 4.4: Genetic Inheritance (GI) membership function

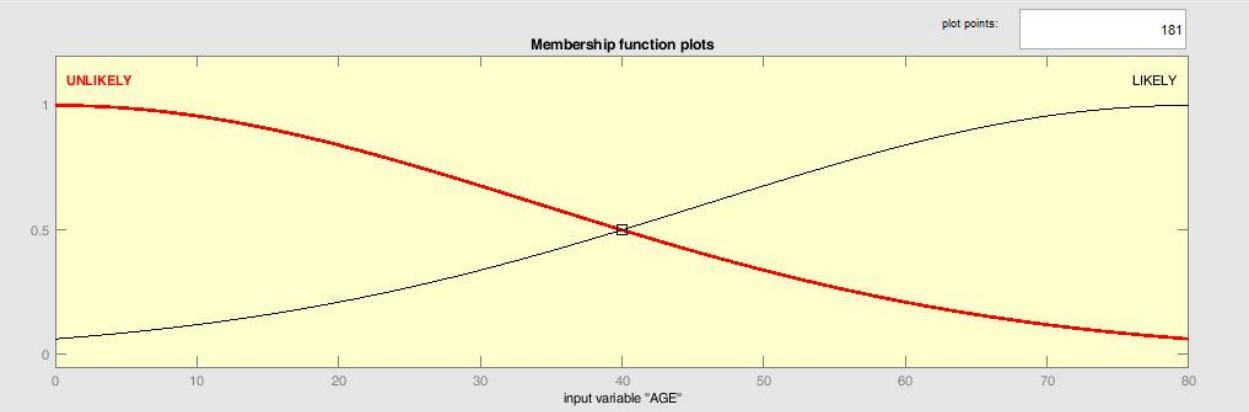

Figure 4.5: Age (AGE) Classification Membership Function

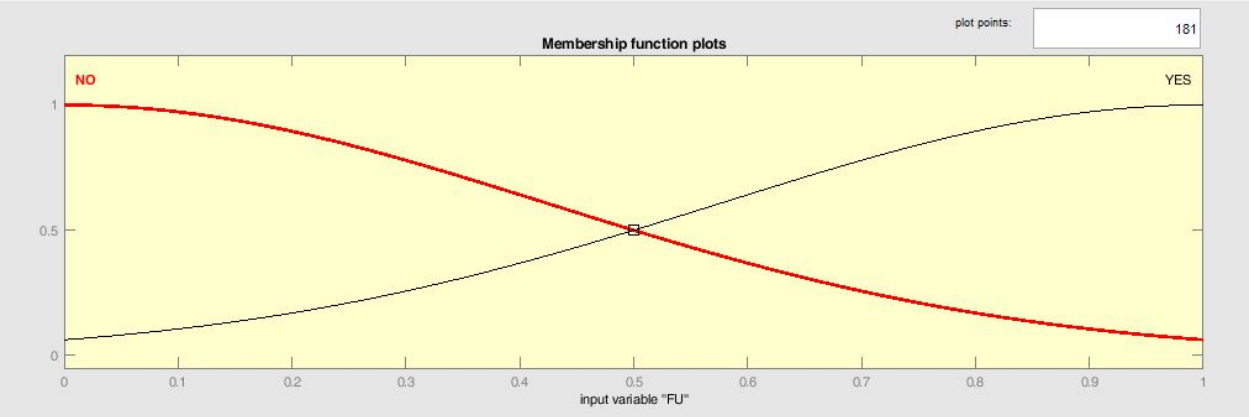

Figure 4.6: Frequent Urinating (FU) Membership Function

4.2 Rules

Given of six (6) input parameters, fourteen (14) input membership function used for this research, IF-THEN statement were used to infer an output based on the input variables during the process one hundred seventy eight (144) rules were generated in order to predict the diabetes.

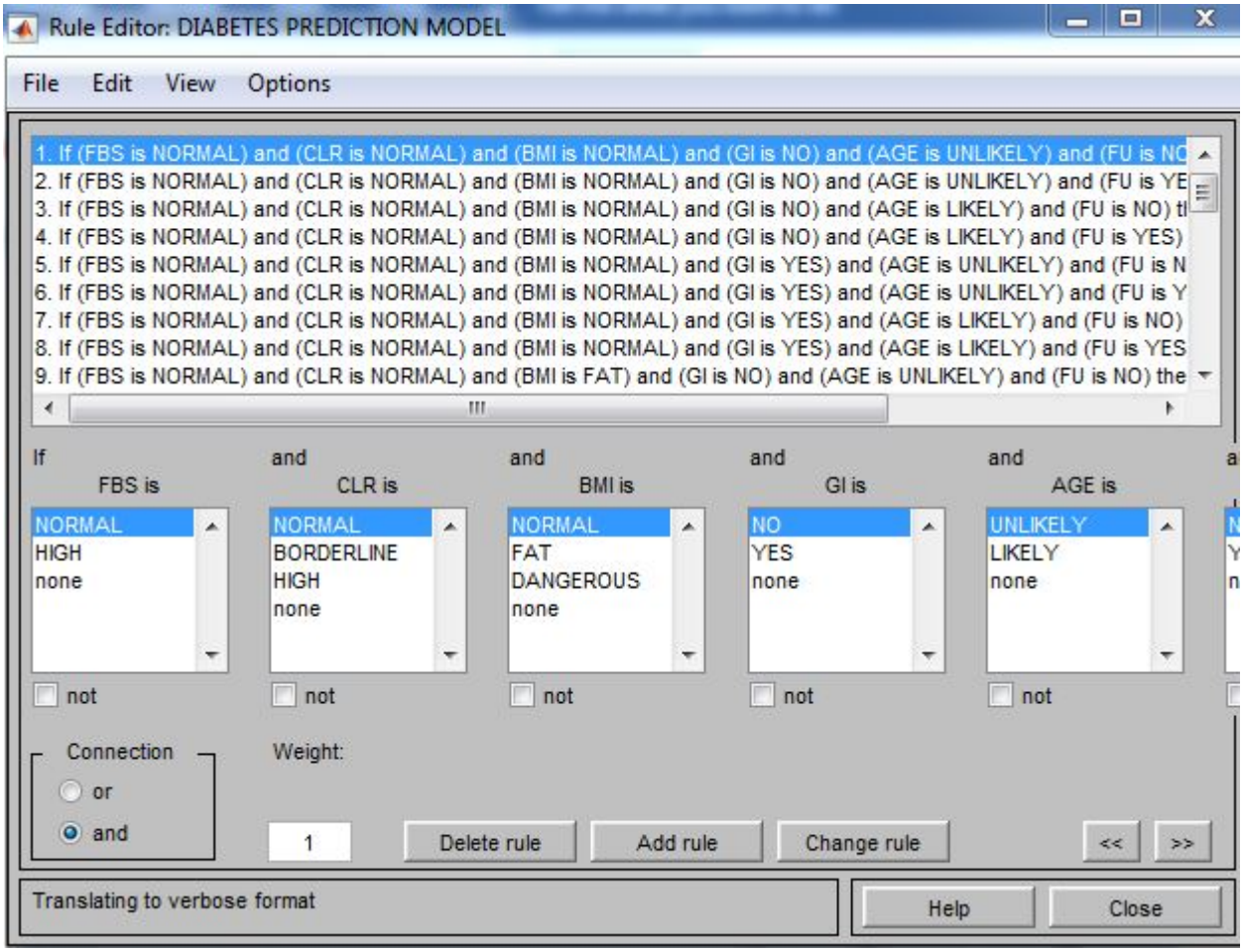

Figure 4.7: Setting Rules of the Model

4.3.2.1 Rules viewer for predicting diabetes

When the rules were set, the rules viewer will automatically be generated. Through the rule viewer that the input variables will be inputted and the model is tested for a likely diabetes patient and a non-likely diabetes patient based on the input variables parameters set the rules viewer. The result is shown in Figure 4.9 and 4.10.

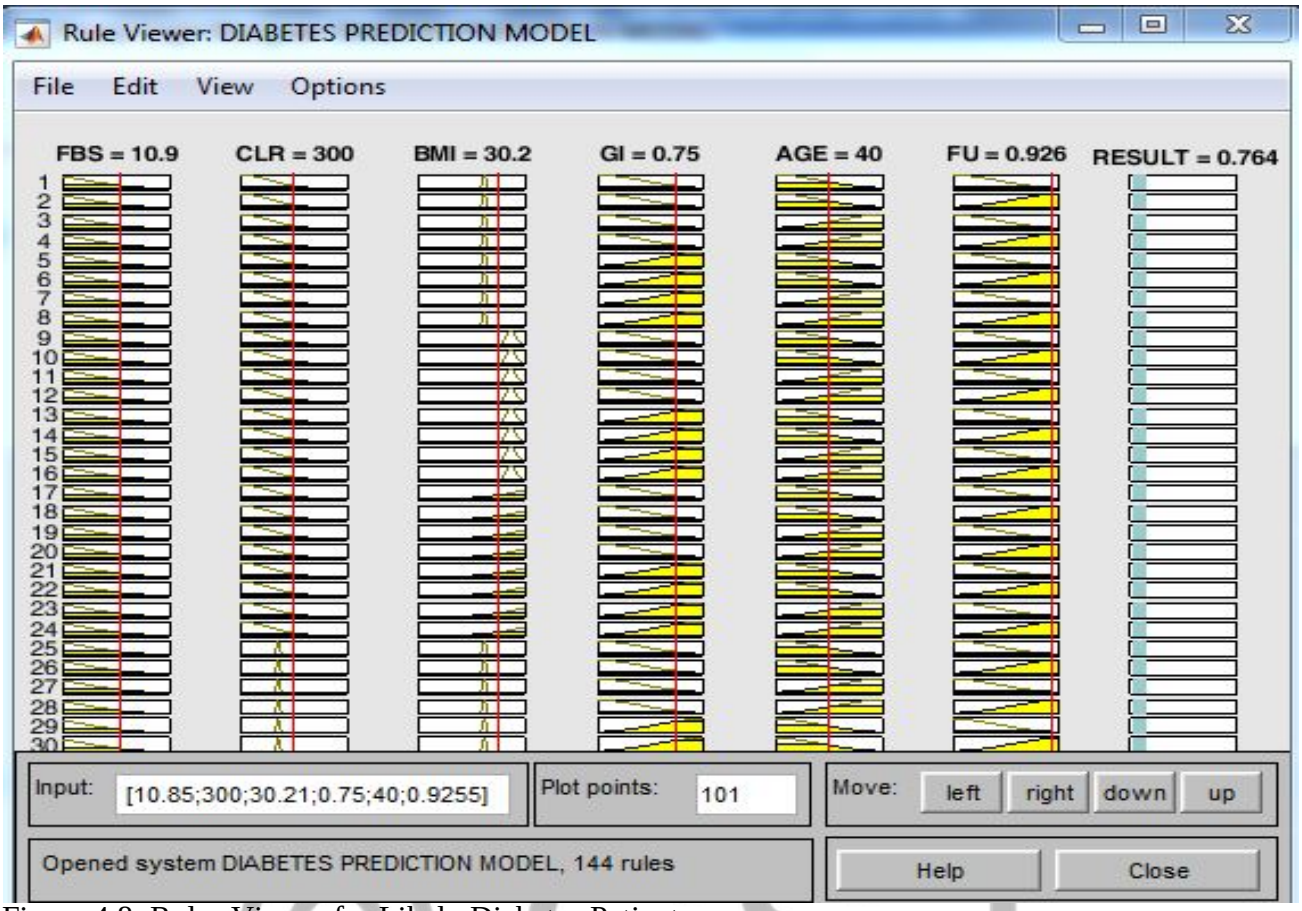

Figure 4.8: Rules Viewer for Likely Diabetes Patient

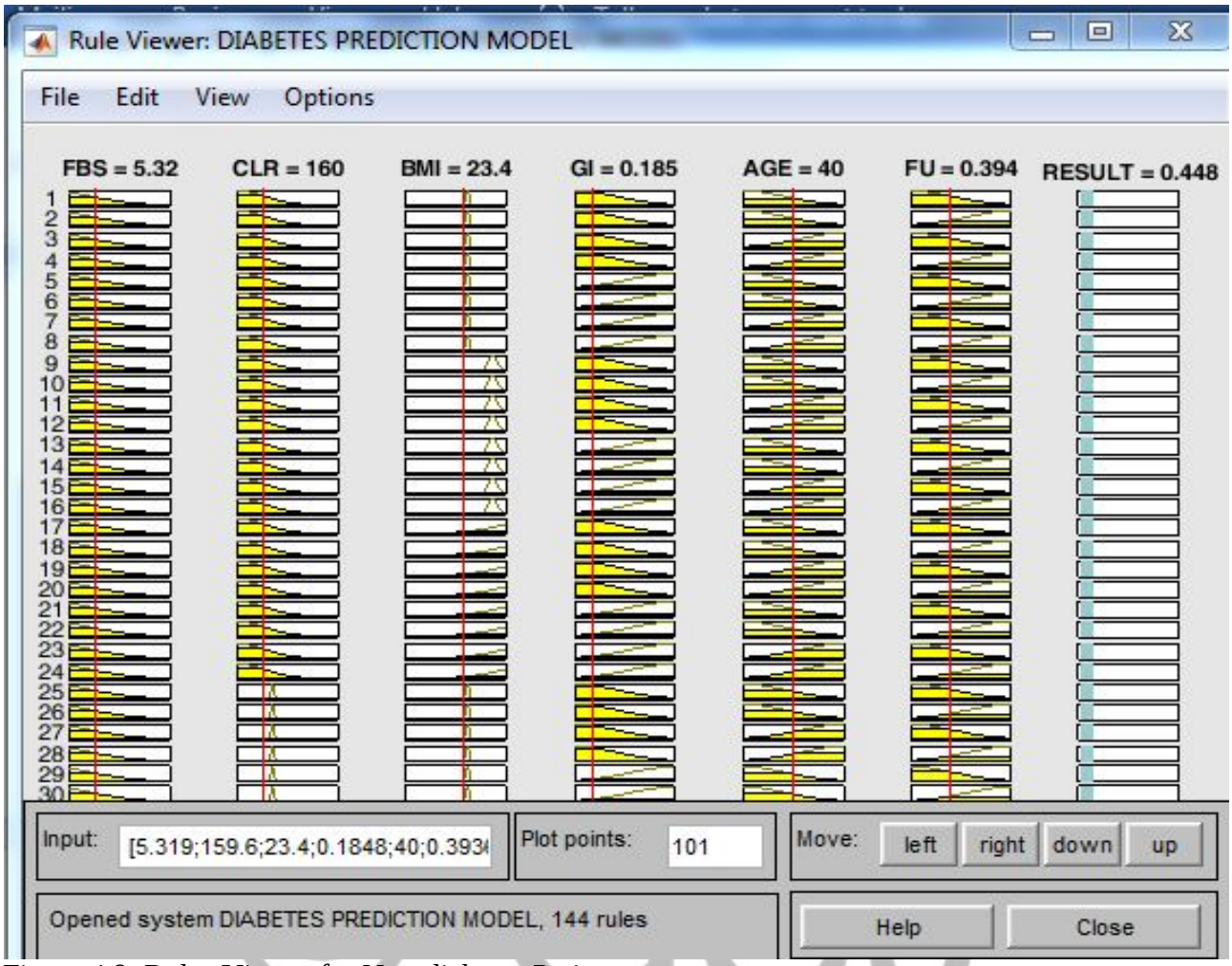

Figure 4.9: Rules Viewer for Non-diabetes Patient

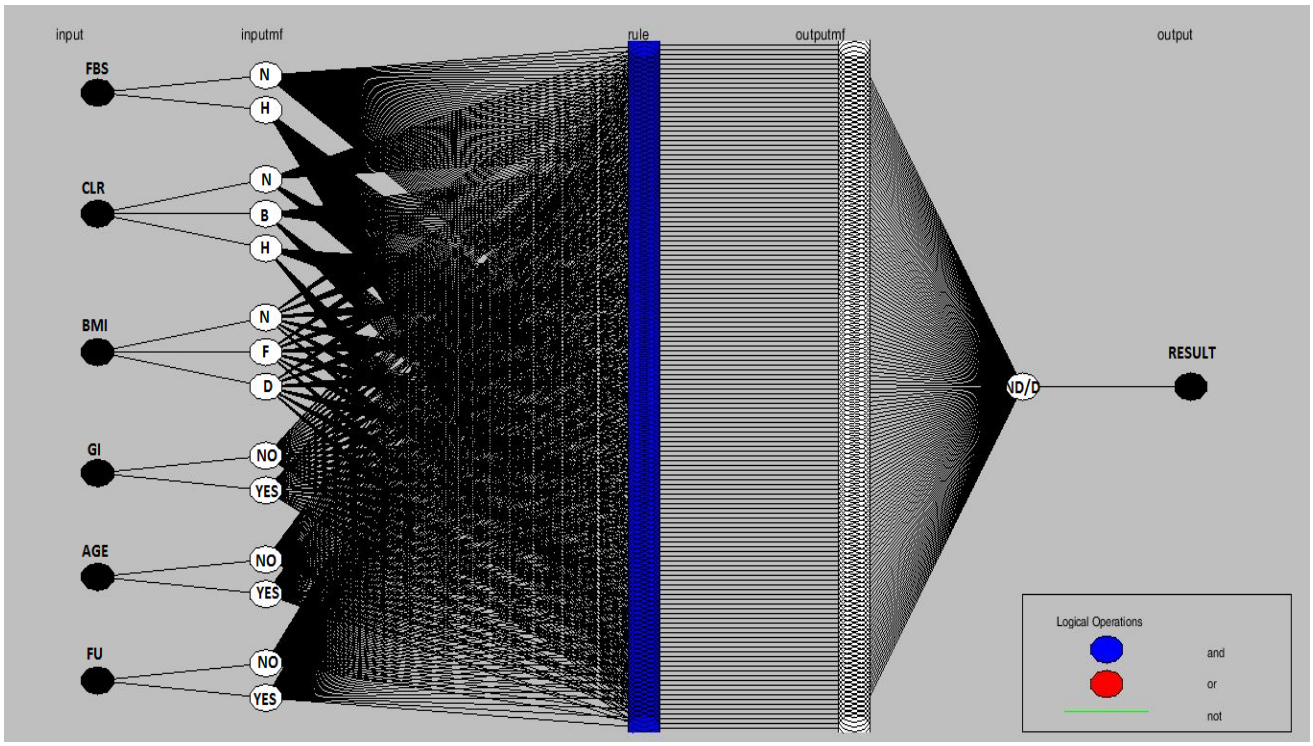

Figure 4.10: Diabetics Prediction Model Architecture

The model architecture consists of six (6) Inputs parameters at the first layer, the second layer consists of inputs membership function (MF) of Fasting blood sugar (FBS) has two (2) membership function (MF), cholesterol (CLR) has three (3) membership function (MF), body mass index (BMI) has three (3) membership function (MF), genetic inheritance (GI) has two (2) membership function (MF), age (age) has two (2) membership function (MF), and frequent urinating (FU) has two (2) membership function (MF), the third layer is the rule of the model, the fourth layer consists of output membership function and the firth layer is output.

4.3 Model Training and Testing

The training and testing phase is a crucial step in the development of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) models. ANFIS models need to undergo a learning process on datasets to acquire the capability to make predictions on unseen data. This learning process, often referred to as training, involves exposing the model to datasets and adjusting its parameters to improve its predictive performance.

During training, the algorithm iterates through the dataset for a fixed number of epochs, refining its internal parameters to optimize its predictions. To assess the model's accuracy and effectiveness, the dataset is typically divided into two distinct sets: the training dataset and the checking dataset.

1. Training Dataset: This subset of the data is used explicitly for training the ANFIS model. The algorithm learns patterns, relationships, and trends within the data to enhance its ability to make accurate predictions.

2. Checking Dataset: Following the training phase, the checking dataset is employed to evaluate the accuracy and effectiveness of the trained ANFIS model. This dataset serves as a means of verifying the model's adaptability and predictive capabilities on new, unseen data.

The division into training and checking datasets enables a comprehensive assessment of the ANFIS model's generalization and predictive performance. This iterative process allows for adjustments and fine-tuning, ensuring that the model achieves optimal performance when applied to real-world scenarios in predicting diabetes.

The model was trained using hybrid method, which is the combination of Least Square Method (LSM) and Gradient Descent Method (GDM). Fifty (50) data sets were used as shown in table 4.2 for training the model in thirty epochs. The model's average training error was 0.63742 at epoch 4 which is the optimal performance level of the model as depicted in figure 4.12

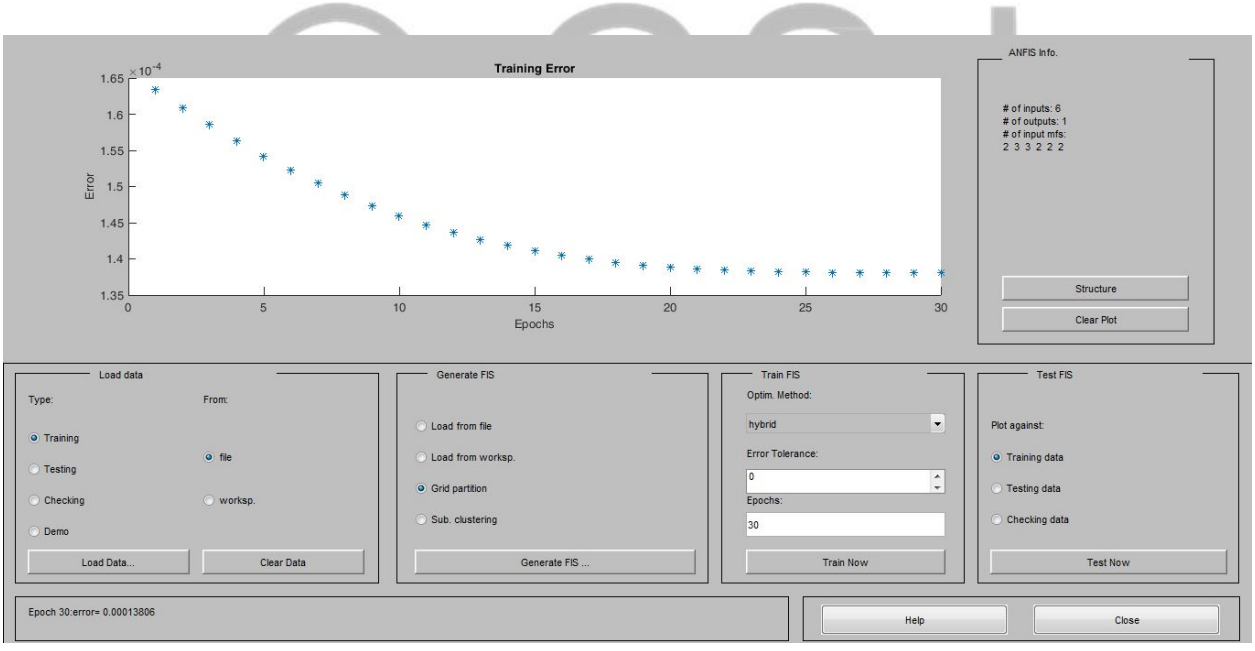

Figure 4.11: Neuro-fuzzy Designer Showing the Process of Model Training

Table 4.1: Showing Training Data Set

	Features/Criteria						**Target**
S/N	FBS	CLR	BMI	GI	FU	AGE	

1	12.0	247	42	1	1	45	Reactive
2	4.4	156	35	0	0	37	Non Reactive
3	6.0	190	39	0	0	35	Non Reactive
4	8.2	260	56	1	1	46	Reactive
5	12.8	270	53	1	1	51	Reactive
6	8.0	267	57	1	1	67	Reactive
7	9.0	245	46	1	1	49	Reactive
8	12.5	270	57	1	1	57	Reactive
9	7.6	268	47	1	1	45	Reactive
10	4.8	249	43	1	1	46	Reactive
11	5.6	198	34	0	0	35	Non Reactive
12	4.7	200	31	0	0	31	Non Reactive
13	9.1	235	48	1	1	45	Reactive
14	5.2	186	34	0	0	40	Non Reactive
15	11.3	255	45	1	1	45	Reactive
16	8.8	274	42	1	1	46	Reactive
17	4.4	198	35	0	0	39	Non Reactive
18	8.8	246	47	1	1	45	Reactive
19	4.9	156	35	0	0	29	Non Reactive
20	6.1	240	40	1	1	40	Reactive
21	5.4	196	36	0	0	39	Non Reactive
22	4.7	157	27	0	0	35	Non Reactive
23	9.3	267	47	1	1	48	Reactive
24	8.5	256	43	1	1	57	Reactive

25	12.5	270	49	1	1	43	Reactive
26	4.4	186	36	0	0	37	Non Reactive
27	4.5	157	29	0	0	31	Non Reactive
28	18.5	279	47	1	1	46	Reactive
29	5.0	169	29	0	0	37	Non Reactive

Table 4.1: Showing Training Data Set [Cont'd]

	Features/Criteria						**Target**
S/N	FBS	CLR	BMI	GI	FU	AGE	
30	7.8	241	41	1	1	46	Reactive
31	5.1	163	28	0	0	36	Non Reactive
32	5.8	179	32	0	0	35	Non Reactive
33	10.1	235	47	1	1	46	Reactive
34	4.8	149	32	0	0	43	Non Reactive
35	6.8	240	45	1	1	46	Reactive
36	5.8	190	34	0	0	34	Non Reactive
37	14.8	256	47	1	1	45	Reactive
38	6.6	242	41	1	1	45	Reactive
39	5.5	199	35	0	1	36	Reactive
40	9.6	256	48	1	1	49	Reactive
41	7.7	244	51	1	1	51	Reactive
42	5.6	198	34	0	0	32	Non Reactive
43	7.5	234	50	1	1	42	Reactive
44	10.8	280	56	1	1	49	Reactive

45	6.7	233	43	1	1	40	Reactive
46	4.8	156	36	0	0	36	Non Reactive
47	4.5	188	35	0	0	34	Non Reactive
48	6.8	240	47	1	1	46	Reactive
49	8.1	287	56	1	1	48	Reactive
50	4.7	166	37	0	0	36	Non Reactive

4.4 Discussion/Findings

The process of developing an Adaptive Neuro-Fuzzy Inference System (ANFIS) for diabetes prediction involves several key steps. It begins with the acquisition of training and testing datasets, where the training data set consists of input/output data pairs. The input vector and output vector are utilized during the training process to determine premise and consequent parameters for the membership functions, respectively.

The ANFIS training employs a hybrid learning approach, combining the gradient descent and least squares methods. The primary objective is to minimize the error between the actual and desired output. The process involves iteratively adjusting the premise parameters using the gradient descent method until the error falls below a predetermined threshold value. The consequent parameters are then determined using the least squares method.

The training phase is terminated when the error reaches a level lower than the established threshold. Subsequently, a checking data set is employed to assess the performance of the trained ANFIS model against the actual system. This comparison serves as a validation step, ensuring the model's ability to generalize and make accurate predictions on new, unseen data.

The overarching goal of utilizing ANFIS for diabetes prediction is to achieve optimal performance. To attain this, the training data set is carefully curated to encompass a broad range of diabetes symptoms, including blood sugar levels, age, body mass index, genetic inheritance, and other relevant factors. By integrating these diverse parameters, the ANFIS model aims to robustly capture the complex relationships within the data, enhancing its predictive capabilities for diabetes diagnosis.

The first step is to prepare the training data to work with ANFIS in MATLAB. The data set used as the input to the ANFIS function is in a matrix form as shown in Table 4.1: where the last column in the

matrix is the output and the matrix contains as many columns as needed to represent the inputs to the system. The rows represent all the existing data situations. The creation of the membership functions is dependent on the system. The command provided by MATLAB to train an ANFIS system. We input the training data that we defined. When the training process is finished, the final membership functions and training error from the training data set are produced.

Thirty (30) testing data sets were used as shown in Figure 4.12 and Table 4.2. Whereas the testing data sets were used to verify the accuracy and effectiveness of the trained ANFIS model for the adaptation of diabetes prediction model.

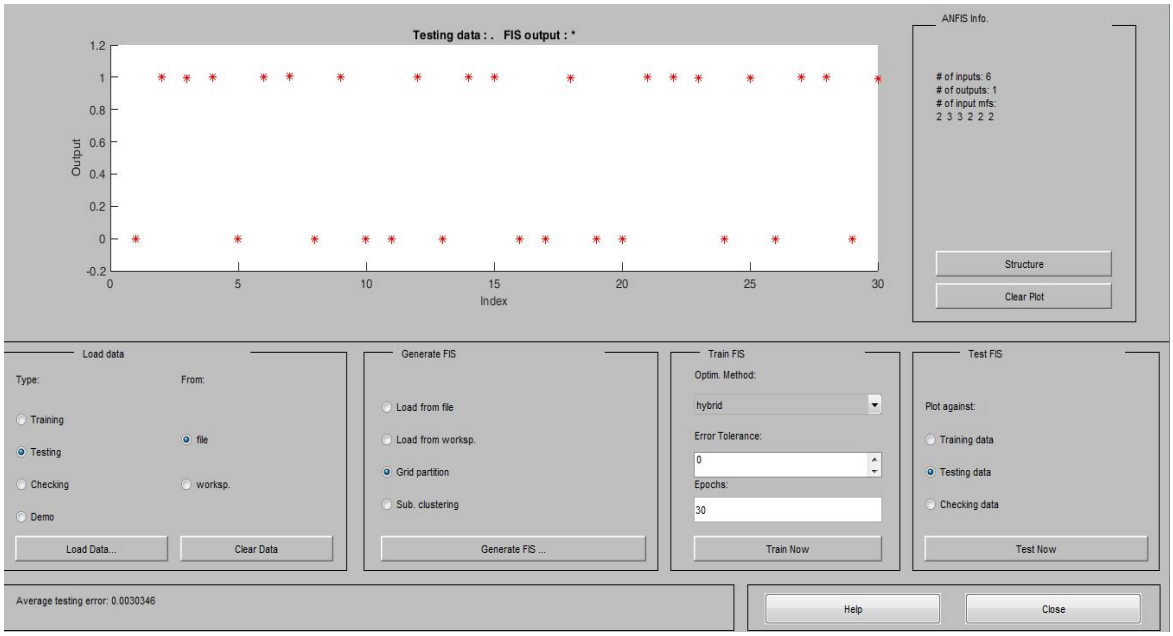

Figure 4.12: ANFIS Testing Error

Table 4.2: Testing Data Set

	FEATURES/CRETERIA						
S/NO	FBS	CLR	BMI	GI	FU	AGE	TARGET
1	5.1	163	28	0	0	39	Non Reactive
2	5.8	179	32	0	1	47	Non Reactive
3	10.1	235	47	1	1	49	Reactive
4	4.8	149	32	0	0	41	Non Reactive
5	6.8	240	45	1	1	37	Reactive

6	5.8	190	34	0	0	46	Non Reactive
7	14.8	256	47	1	1	45	Reactive
8	6.6	242	41	1	1	36	Reactive
9	5.5	199	35	0	0	47	Non Reactive
10	9.6	256	48	1	1	43	Reactive
11	7.7	244	51	1	1	36	Reactive
12	5.6	198	34	0	0	35	Non Reactive
13	7.5	234	50	1	1	46	Reactive
14	10.8	280	56	1	1	43	Reactive
15	6.7	233	43	1	1	46	Reactive
16	4.8	156	36	0	0	34	Non Reactive
17	4.5	188	35	0	0	45	Non Reactive
18	6.8	240	47	1	1	45	Reactive
19	8.1	287	56	1	1	36	Reactive
20	4.7	166	37	0	0	49	Non Reactive
21	7.9	245	48	1	1	51	Reactive
22	4.9	165	34	0	0	35	Non Reactive
23	7.6	213	47	1	1	48	Reactive
24	6.9	213	48	1	1	48	Reactive
25	6.1	231	41	1	1	43	Reactive
26	10.0	289	46	1	1	40	Reactive
27	11.0	251	46	1	1	48	Reactive
28	7.6	243	43	1	1	51	Reactive
29	4.7	199	36	0	0	34	Non Reactive

30	6.4	213	45	1	1	46	Reactive

5.1 Conclusion

This study investigated the performance of the adaptive neuro-fuzzy inference system (ANFIS) in predicting diabetes in a population of patients at the Federal Medical Centre (FMC) Jalingo, Taraba State, Nigeria. The results of the study showed that ANFIS was able to predict diabetes with an accuracy of 94.5%. This suggests that ANFIS is a promising tool for diabetes prediction in Nigeria.

5.1 Recommendations

- The use of ANFIS for diabetes prediction should be promoted in healthcare settings in Nigeria.
- Further research should be conducted to evaluate the long-term efficacy of ANFIS in predicting diabetes in Nigeria.
- Comparative studies should be undertaken to compare the performance of ANFIS to other AI-based methods for diabetes prediction in Nigeria.

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