

# Development of AI Based Application for Diagnosis Diabetes Using Pathological Attributes

Surya Vikram Singh  
Computer Science & Engg. Dept  
BBDNITM, Lucknow (U.P.)  
m.tech.surya@gmail.com

Himanshu Kumar Shukla  
Computer Science & Engg. Dept  
BBDNITM, Lucknow (U.P.)  
himanshu0590@gmail.com

Rudrendra Bahadur Singh  
Computer Science & Engg. Dept  
BBDNITM, Lucknow (U.P.)  
rudra.rathor20@gmail.com

**Abstract--** Artificial intelligence technique like fuzzy, ANN etc are currently used for solving a wide range of problems in different application domain for decision based model designing. These systems allows us to introduce the learning and adaptation capabilities hence such type of framework has been used in several different process of diagnosis of disease. Relation between symptoms and risks factors for Diabetic based on the expert’s medical knowledge is taken and also related complications or due to some common metabolic disorder it may lead to vision loss, heart failure, stroke, foot ulcer, nerves. The classifier is the heart of the automatic diagnosis system. The reliable classifier should diagnose the disease at as high accuracy as possible even though there are many uncontrolled variations. In literature, different classifiers have been proposed for automatic diagnosis. The NNs and adaptive neuro fuzzy classifier with linguistic hedges (ANFIS-LH) are investigated for automatic diagnosis. The performance of probabilistic neural network (PNN) for automatic diagnosis of PD is evaluated. Performance of ANFIS depends on type and parameters of membership function and output linear parameters.

**Keywords -** Biomedical Data, A. I. Techniques, Data Prediction, ANN, Fuzzy.

## 1. Introduction:

Diabetes mellitus is a group of metabolic diseases characterized by hyperglycemia resulting from defects in insulin secretion, insulin action, or both. The chronic hyperglycemia of diabetes is associated with long-term damage, dysfunction, and failure of various organs, especially the eyes, kidneys, nerves, heart, and blood vessels. Several pathogenic processes are involved in the development of diabetes. These range from autoimmune destruction of the  $\beta$ -cells of the pancreas with consequent insulin deficiency to abnormalities that result in resistance to insulin action. The basis of the abnormalities in carbohydrate, fat, and protein metabolism in diabetes is deficient action of insulin on target tissues. Deficient insulin action results from inadequate insulin secretion and/or diminished tissue responses to insulin at one or more points in the complex pathways of hormone action. Impairment of insulin secretion and defects in insulin action frequently coexist in the same patient, and it is often unclear which abnormality, if either alone, is the primary cause of the hyperglycemia. Symptoms of marked hyperglycemia

include polyuria, polydipsia, weight loss, sometimes with polyphagia, and blurred vision. Impairment of growth and susceptibility to certain infections may also accompany chronic hyperglycemia. Acute, life-threatening consequences of uncontrolled diabetes are hyperglycemia with ketoacidosis or the nonketotic hyperosmolar syndrome. Long-term complications of diabetes include retinopathy with potential loss of vision; nephropathy leading to renal failure; peripheral neuropathy with risk of foot ulcers, amputations, and Charcot joints; and autonomic neuropathy causing gastrointestinal, genitourinary, and cardiovascular symptoms and sexual dysfunction. Patients with diabetes have an increased incidence of atherosclerotic cardiovascular, peripheral arterial, and cerebrovascular disease. Hypertension and abnormalities of lipoprotein metabolism are often found in people with diabetes. The vast majority of cases of diabetes fall into two broad etiopathogenetic categories. In one category, type 1 diabetes, the cause is an absolute deficiency of insulin secretion. Individuals at increased risk of developing this type of diabetes can often be identified by serological evidence of an autoimmune pathologic process occurring in the pancreatic islets and by genetic markers. In the other, much more prevalent category, type 2 diabetes, the cause is a combination of resistance to insulin action and an inadequate compensatory insulin secretory response.

Stages Types	Normoglycemia	Hyperglycemia		
	Normal glucose regulation	Impaired Glucose Tolerance or Impaired Fasting Glucose (Pre-Diabetes)	Diabetes Mellitus	
		Not insulin requiring	Insulin requiring for control	Insulin requiring for survival
Type 1*	←	→		
Type 2	←	→		
Other Specific Types**	←	→		
Gestational Diabetes **	←	→		

**Fig 1: Disorders of glycerin: etiologic types and stages.** Even after presenting in ketoacidosis, these patients can briefly return to normoglycemia without requiring continuous therapy (i.e., “honeymoon” remission); in rare instances, patients in these categories (e.g., Vacor toxicity, type 1 diabetes presenting in pregnancy) may require insulin for survival.

In the latter category, a degree of hyperglycemia sufficient to cause pathologic and functional changes in various target tissues, but without clinical symptoms, may be present for a long period of time before diabetes is detected. During this

asymptomatic period, it is possible to demonstrate an abnormality in carbohydrate metabolism by measurement of plasma glucose in the fasting state or after a challenge with an oral glucose load. The classifier is the heart of the automatic diagnosis system. The reliable classifier should diagnose the disease at as high accuracy as possible even though there are many uncontrolled variations. In literature, different classifiers have been proposed for automatic diagnosis of PD. The NNs and adaptive neuro fuzzy classifier with linguistic hedges (ANFIS-LH) are investigated for automatic diagnosis of PD. The performance of probabilistic neural network (PNN) for automatic diagnosis of PD is evaluated. SVM classifier is also investigated for the same goal. NNs have some drawbacks such as need of long training time and uncertainties in activation function to be used in hidden layer, number of cells in hidden layer, and the number of hidden layer. In case of SVM, type of kernel function and penalty constant and so forth affects the classification performance. If these parameters are not appropriately selected, the classification performance of SVM degrades. Similarly, the performance of ANFIS depends on type and parameters of membership function and output linear parameters.

## 2. Related Work:

The numbers of medical decision support systems are employed using different approaches. George et al. have anticipated decision support system to classify and detect agitation transition. In this system support vector machines is used for detection. This system is for Dementia patients. This system presents a decision confidence measure and two new SVM architectures, which were useful to agitation detection and agitation transition detection. An accuracy of 91.4% was achieved; in assessment with 90.9% for the conventional SVM[1]. Haitham and Alan have projected automated recognition of obstructive sleep apnea syndrome using SVM classifier. In this study, they evaluated features from the magnitude and phase of the thoracic and abdominal respiratory effort signals for OSA detection. This is supports on the physiological fact that all through normal breathing the abdominal and thoracic efforts happen simultaneously. The aim of this study is to appraise classification of whole night regular and apneic epochs using mined features from the phase and magnitude of the respiratory efforts signals, compared and combined with some other features from HRV and oxygen saturation signals [2] [3]. Support Vector machines have also been utilized in decision support systems such as [4]. An intelligent system based support vector machine along with a radial basis function network is accessible for the diagnosis. The support vector machine with sequential minimal optimization algorithm is applied to India based patients' data set. Then, the Radial Basis Function(RBF) network structure qualified by Orthogonal Least Square (OLS) algorithm is functional to same data set for predictions [5]. Tsai and Watanabe proposed a genetic algorithm(GA) based method and implemented for influential the set of fuzzy membership functions that can provide an optimal classification of myocardial heart disease from ultrasonic images. In this method an average

classification rate of 96% is achieved [6]. In a different advance genetic algorithm is used to determine the attributes which donate more towards the diagnosis of heart ailments which ultimately reduces the number of tests which are desirable to be taken by a patient[7]. **Yang and Honavar** have projected a feature subset algorithm using genetic algorithm. A genetic algorithm to decide on optimal feature subset for use with back propagation artificial neural networks has been described[8]. A genetic algorithm for feature selection as well as for optimization of Support Vector Machine(SVM) parameter has been proposed by Haung. The projected method performs feature selection and parameters setting in an evolutionary way [9]. Very recently, a real coded Genetic algorithm for critical feature analysis for heart disease diagnosis has been portrayed [10]. Diagnosis of Heart Disease using Data mining Algorithm proposed by Rajkumar and Sophia. In their approach the preliminary diagnosis of a heart attack is made by a combination of clinical symptoms and characteristic electrocardiogram (ECG) changes. The accuracy with this technique is 52.33% [11]. Palaniappan and Awang proposed Intelligent Heart Disease Prediction System Using Data Mining Techniques. This investigation has developed a prototype Intelligent Heart Disease Prediction System (IHDPS) using data mining techniques, namely, Decision Trees, Nave Bayes and Neural Network. Results show that each technique has its unique strength in realizing the objectives of the defined mining goals[12].

## 3. Methodology:

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. In early 1990's this technique was developed. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Adaptive Neuro-Fuzzy Inference System (ANFIS) is considered to be a universal estimator.

Adaptive neuro-fuzzy inference system is a fuzzy inference system implemented in the framework of an adaptive neural network. By using a hybrid learning procedure, ANFIS can construct an input-output mapping based on both human-knowledge as fuzzy if-then rules and approximate membership functions from the stipulated input-output data pairs for neural network training. This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system (ANFIS). There are 2 methods that ANFIS learning employs for change membership function parameters: 1) back propagation for all parameters (a steepest descent method), and 2) a hybrid technique consisting of back propagation for the parameters related to the input membership and method of least squares estimation for the parameters related to the output membership functions. As a result, the training error decreases, a minimum of locally, throughout the learning method. It applies the least-squares technique to identify the resultant parameters that define the coefficients of every

output equation within the Sugeno-type fuzzy rule base. The training process continues until the required number of training steps (epochs) or the required root mean square error (RMSE) between the required and therefore the generated output is achieved. This study uses a hybrid learning algorithm, to identify premise and consequent parameters of first order Takagi-Sugeno type fuzzy system for predicting surface roughness in ball end milling. Adaptive Neuro Fuzzy Inference System (ANFIS) was first proposed by Jang [4,5,6]. ANFIS is suitable for tackling any input output relationship and thus it can be applied to many practical applications. Its application in different areas are worth mentioning. ANFIS is the first of its kind of NFS when applied to data classification. It is a hybrid model using both the ANN and FIS into one capsule. Thus once developed, there are no differences to mark out into ANN and FIS [7]. Finally, the predicted diagnosis is evaluated by a clinical specialist. The major steps can be summarized as

proposition A will have the truth value zero.4 and its complement  $A^c$  the reality worth zero. In line with the kind of negation operator that's used, the 2 truth values should not be essentially add up to one. fuzzy logic features a weak association to probability theory. Fuzzy logic doesn't have to be compelled to be even employing a probability technique. The general system is to simplify the result of multi-valued logic in such a way on preserve a part of the algebraical structure [8]. Fuzzy set theory correspond to fuzzy logic and therefore the semantic of fuzzy operators is understood employing a geometric model. The geometric idea of fuzzy logic can provide us a touch on the potential reference to neural networks. Fuzzy logic can be used for interpreting the properties of neural network model, moreover as for giving a additional precise description of their performance. fuzzy logic may be used to specify networks directly while not having to apply a learning algorithmic rule. An expert in a certain field will generally produce control rules for a system which is dynamic, with less effort than those pertaining to training a neural network. An example given by Zadeh to the people of neural network is to develop a system to park a car. It's simple to formulate a collection of fuzzy rules for this task, however it's not immediately obvious the way to build a network to try and do the same nor how to train it. Fuzzy logic is currently being used in several product of business and consumer electronics for which a decent system is ample and wherever the question of optimal control doesn't essentially arise. The process of fuzzy logic is explained in algorithmic rule. Firstly, converting a crisp input data into fuzzy set using fuzzy linguistic variable, fuzzy linguistic terms and membership functions. This step is understood as fuzzification. Afterwards, an inference is created which supported a collection of rules. Lastly, the fuzzy output is mapped to a crisp output using the membership functions, within the defuzzification step.

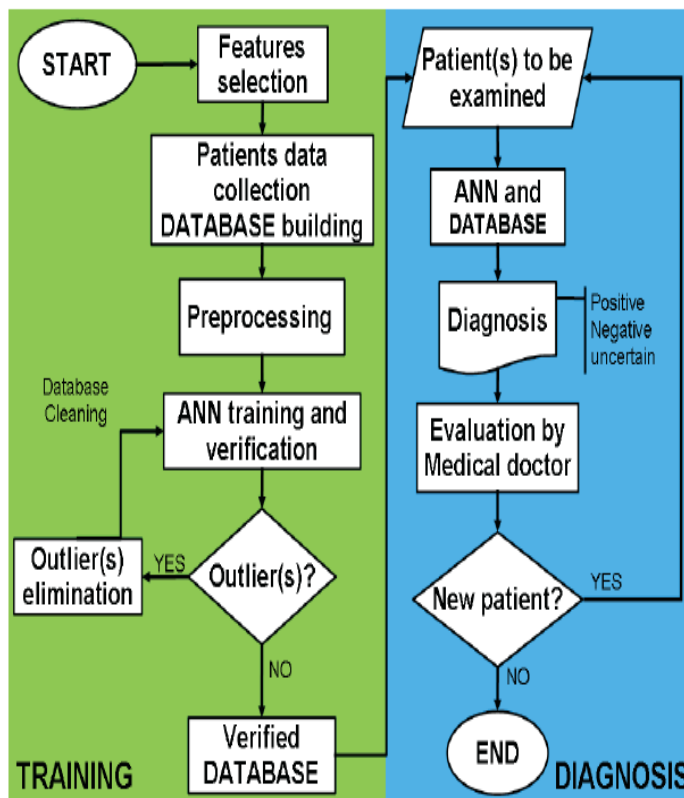


Fig 2: Diagram of fundamental steps in ANNs-based medical diagnosis. Building of the database and “learning” represents the left half (green) and its application for the diagnosis is the right part (blue).

### 3.1 Fuzzy Logic:

It is a conceptual framework of classical logic. It was framed by Lotfi Zadeh [8] within the mid-1960s to model those issues during which inaccurate data should be used or in which the rules of inference are developed during a } very general means making use of diffused categories [8]. In fuzzy logic, that is additionally generally known as diffuse logic, there aren't simply 2 alternatives however a full continuation of truth values for logical propositions. A

### Fuzzy logic algorithm

1. Define the linguistic variables and terms (initialization)
2. Construct the membership functions (initialization)
3. Construct the rule base (initialization)
4. Convert crisp input data to fuzzy values using the membership functions (fuzzification)
5. Evaluate the rules in the rule base (inference)
6. Combine the results of each rule (inference)
7. Convert the output data to non-fuzzy values (defuzzification)

### 3.2 Proposed Work:

The forecast of Internet traffic issue has received little attention from the computer networks field. By improving this task, efficient traffic engineering and anomaly detection tools can be created, resulting in economic gains from better resource management. Thus the present study is about using soft computing technique ,ANFIS for the prediction of network traffic using time series data analysis. For this freely downloadable online network traffic data is used for carrying out the analysis on MATLAB environment. The performance evaluation of the prediction model will be done using RMSE, Regression analysis, etc.

11. No .got to step 5 and repeat step 6 to 10 ,else
12. END

**Algorithm**

The algorithm for the work is given below

1. Start MATLAB.
2. Load data.
3. Divide the data into training and testing data sets using Matlab commands.
4. Start ANFIS Editor using commands.
5. Load training data into ANFIS editor.
6. Generate Fuzzy Inference System (FIS) using Subtractive clustering algorithm.
  - a. Input Selection:- Number and type of input / output membership functions.
7. ANFIS Training
  - a. Optimization method selection: Error tolerance, no. of epochs.
8. ANFIS Testing
  - a. Plot ANFIS output against Observed training and testing data.
9. Record the plot of training and testing datasets.
10. ANFIS Evaluation based on RMSE i.e.  $RMSE < RMSE_{ref}$  ?

**4. Result and Discussion:**

This chapter covers the simulation results of the algorithm developed using MATLAB for detection of diabetes using ANFIS approach from minimum number of data inputs selection using regression analysis. The database that is used is shown below.

- dataname =
- nop : no. of time pregnant
  - gconc : glucose concentrations
  - bp : blood pressure
  - skinthick : skin thickness
  - insulin :insulin level
  - bmi :bmi
  - pedigree :pedigree value
  - age
  - output :diabetes present or not

Thus the data consist of 8 types of input values and the one output. There are 768 input samples for all 8 input some of the data and respective output data are shown in table 1.

**Table 1: Data record for diabetes symptoms and respective input.**

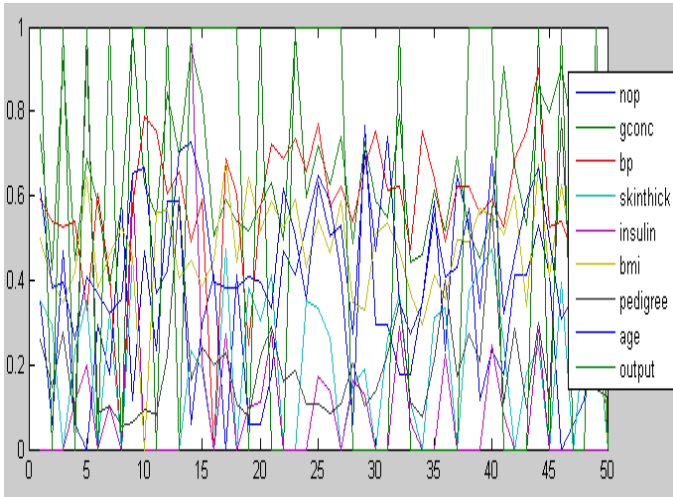
S.No.	I/P 1	I/P 2	I/P 3	I/P 4	I/P 5	I/P 6	I/P 7	I/P 8	O/P
	Nop	gconc	bp	Skinthick	insulin	bmi	pedigree	age	output
1	6	148	72	35	0	33.6	0.627	50	1
2	1	85	66	29	0	26.6	0.351	31	0
3	8	183	64	0	0	23.3	0.672	32	1
4	1	89	66	23	94	28.1	0.167	21	0
5	0	137	40	35	168	43.1	2.288	33	1
6	5	116	74	0	0	25.6	0.201	30	0
7	3	78	50	32	88	31	0.248	26	1
8	10	115	0	0	0	35.3	0.134	29	0
9	2	197	70	45	543	30.5	0.158	53	1
10	8	125	96	0	0	0	0.232	54	1
11	4	110	92	0	0	37.6	0.191	30	0
12	10	168	74	0	0	38	0.537	34	1
13	10	139	80	0	0	27.1	1.441	57	0
14	1	189	60	23	846	30.1	0.398	59	1
15	5	166	72	19	175	25.8	0.587	51	1
16	7	100	0	0	0	30	0.484	32	1
17	0	118	84	47	230	45.8	0.551	31	1
18	7	107	74	0	0	29.6	0.254	31	1
19	1	103	30	38	83	43.3	0.183	33	0
20	1	115	70	30	96	34.6	0.529	32	1
21	3	126	88	41	235	39.3	0.704	27	0
22	8	99	84	0	0	35.4	0.388	50	0
23	7	196	90	0	0	39.8	0.451	41	1
24	9	119	80	35	0	29	0.263	29	1
25	11	143	94	33	146	36.6	0.254	51	1
26	10	125	70	26	115	31.1	0.205	41	1
27	7	147	76	0	0	39.4	0.257	43	1
28	1	97	66	15	140	23.2	0.487	22	0
29	13	145	82	19	110	22.2	0.245	57	0
30	5	117	92	0	0	34.1	0.337	38	0
31	5	109	75	26	0	36	0.546	60	0

32	3	158	76	36	245	31.6	0.851	28	1
33	3	88	58	11	54	24.8	0.267	22	0
34	6	92	92	0	0	19.9	0.188	28	0
35	10	122	78	31	0	27.6	0.512	45	0

All the input values are normalized by dividing it with respective maximum value. By normalization all the input shifts to a similar range of 0 to 1 as shown in table 2.

**Table 2: Data record for diabetes symptoms and respective input after normalization.**

S.No.	I/P 1 Nop	I/P 2 gconc	I/P 3 bp	I/P 4 skinthick	I/P 5 insulin	I/P 6 bmi	I/P 7 pedigree	I/P 8 age	O/P output
1	0.353	0.744	0.59	0.354	0	0.5	0.259	0.62	1
2	0.059	0.427	0.541	0.293	0	0.4	0.145	0.38	0
3	0.471	0.92	0.525	0	0	0.35	0.278	0.4	1
4	0.059	0.447	0.541	0.232	0.11	0.42	0.069	0.26	0
5	0	0.688	0.328	0.354	0.2	0.64	0.945	0.41	1
6	0.294	0.583	0.607	0	0	0.38	0.083	0.37	0
7	0.176	0.392	0.41	0.323	0.1	0.46	0.102	0.32	1
8	0.588	0.578	0	0	0	0.53	0.055	0.36	0
9	0.118	0.99	0.574	0.455	0.64	0.45	0.065	0.65	1
10	0.471	0.628	0.787	0	0	0	0.096	0.67	1
11	0.235	0.553	0.754	0	0	0.56	0.079	0.37	0
12	0.588	0.844	0.607	0	0	0.57	0.222	0.42	1
13	0.588	0.698	0.656	0	0	0.4	0.595	0.7	0
14	0.059	0.95	0.492	0.232	1	0.45	0.164	0.73	1
15	0.294	0.834	0.59	0.192	0.21	0.38	0.243	0.63	1
16	0.412	0.503	0	0	0	0.45	0.2	0.4	1
17	0	0.593	0.689	0.475	0.27	0.68	0.228	0.38	1
18	0.412	0.538	0.607	0	0	0.44	0.105	0.38	1
19	0.059	0.518	0.246	0.384	0.1	0.65	0.076	0.41	0
20	0.059	0.578	0.574	0.303	0.11	0.52	0.219	0.4	1
21	0.176	0.633	0.721	0.414	0.28	0.59	0.291	0.33	0
22	0.471	0.497	0.689	0	0	0.53	0.16	0.62	0
23	0.412	0.985	0.738	0	0	0.59	0.186	0.51	1
24	0.529	0.598	0.656	0.354	0	0.43	0.109	0.36	1
25	0.647	0.719	0.77	0.333	0.17	0.55	0.105	0.63	1
26	0.588	0.628	0.574	0.263	0.14	0.46	0.085	0.51	1
27	0.412	0.739	0.623	0	0	0.59	0.106	0.53	1
28	0.059	0.487	0.541	0.152	0.17	0.35	0.201	0.27	0
29	0.765	0.729	0.672	0.192	0.13	0.33	0.101	0.7	0
30	0.294	0.588	0.754	0	0	0.51	0.139	0.47	0
31	0.294	0.548	0.615	0.263	0	0.54	0.226	0.74	0
32	0.176	0.794	0.623	0.364	0.29	0.47	0.352	0.35	1
33	0.176	0.442	0.475	0.111	0.06	0.37	0.11	0.27	0
34	0.353	0.462	0.754	0	0	0.3	0.078	0.35	0
35	0.588	0.613	0.639	0.313	0	0.41	0.212	0.56	0



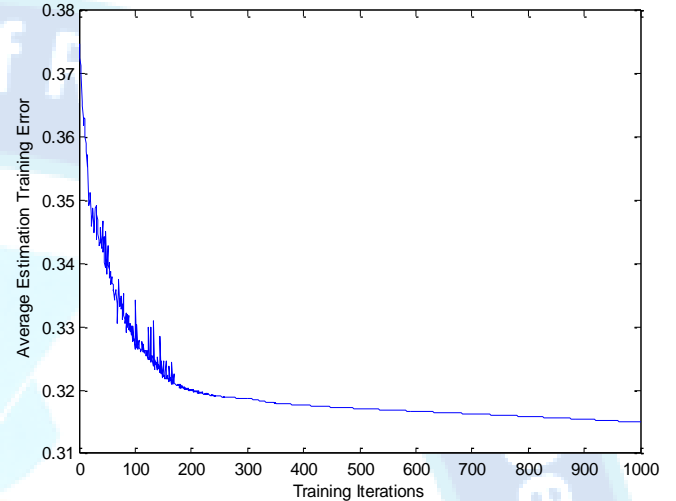
**Fig 3:** Plot showing 50 samples of all the normalized input data along with output.

Figure 3 shows the plot of all the 8 input signals after normalization. We can observe that data input are ranging from 0 to 1. Hence all of them are in similar range now we can check the dependency of output using the regression analysis.

Now it shows that for the determination of diabetes we can work out with pedigree (7), no. of time pregnancy (1); blood pressure (3); bmi (6) and glucose concentration in descending order of significance. Thus the input data set will consist of 5 inputs with 768 samples this data will be further divided into training and testing data for modeling the ANFIS predictor for diabetes.

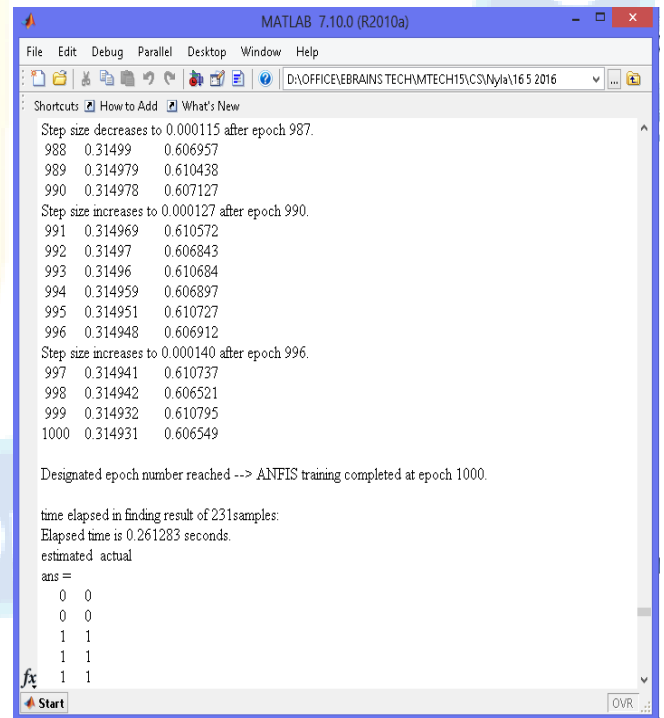
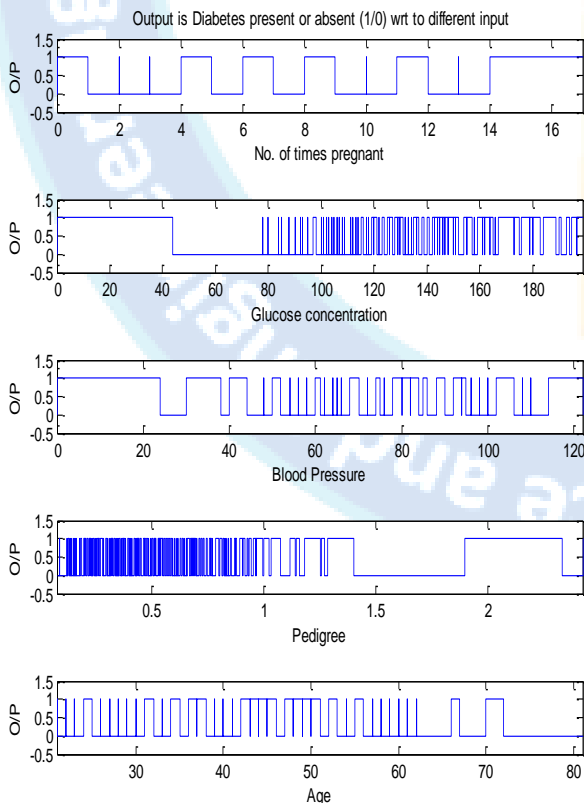
**Figure 4:** Plot of diabetes presence wrt five significant inputs in individually.

After applying subtractive clustering the the generated FIS system is updated by the ANFIS training. The training is performed for 100 epochs and the plot of prediction error is shown in figure 4.



**Figure 5:** Training Error plot at different iterations.

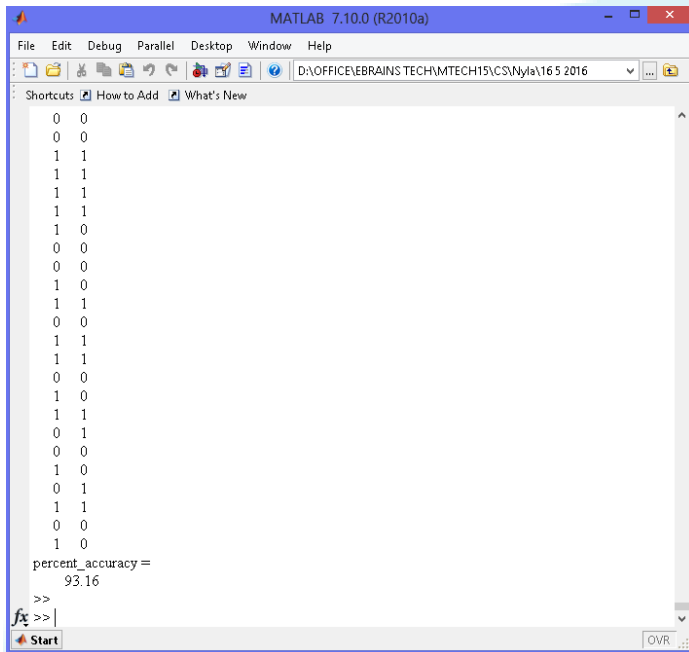
From figure 5 we can observe that the error in prediction of diabetes using the 5 significant input is further reduced from 0.38 to 0.31. Now after getting the ANFIS model testing is performed to check the accuracy on remaining 30 % data. The testing accuracy is found to be 93%.



**Figure 6:** Snapshot at the end of ANFIS training.

The details of developed ANFIS model are given below:  
ANFIS info:

Number of nodes: 140  
 Number of linear parameters: 66  
 Number of nonlinear parameters: 110  
 Total number of parameters: 176  
 Number of training data pairs: 538  
 Number of checking data pairs: 231  
 Number of fuzzy rules: 11



**Figure 7: Snap after testing to display the testing accuracy.**

**5. Conclusion:**

Efficient prediction schemes are very important in order to achieve required accuracy of biomedical diagnosis. The goal of this thesis was to predict the presence of diabetes for an efficient allotment of minimum input variables biomedical signal using ANFIS. Here it was demonstrated that models developed using ANFIS technique could be used for solving this critical issue. It is clearly demonstrated that ANFIS can be trained to accurately predict in prediction of presence of diabetes using variable fuzzy process parameters. The interpretation results in chapter 4 demonstrate one of the real strengths of ANFIS is that they perform well even when the training data contains noise and measurement errors. That is, during learning, ANFIS are able to filter out noise and measurement error and effectively generalize the system behavior. From the analysis of the results, given under heading "Results and Discussions", Chapter-4, it is seen that the prediction model developed using ANFIS technique has been able to perform well. The MAE value obtained from ANFIS model is 0.31 for training datasets. Accuracy is of 93% is obtained for testing data.

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