FRAMEWORK FOR A GENETIC-NEURO-FUZZY INFERENTIAL SYSTEM FOR DIAGNOSIS OF DIABETES MELLITUS

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ABSTRACT: One of the most dangerous diseases in the modern society is diabetes mellitus and it is not only a medical problem but also a socio-economy. Artificial Intelligence techniques have been successfully employed in diabetes disease diagnosis, risk evaluation, patient monitoring, and medicine. Using single techniques in diagnosis of diabetes has been comprehensively investigated showing some level of accuracy. Researchers have investigated the effect of hybridizing more than one technique to show enhance results in the diagnosis of diabetes. However, using the combination of two or more technique to identify a suitable treatment for diagnosis of diabetes patients has received less attention. Therefore, in this work, a framework for three intelligent approaches will be used to develop an expert system using Genetic, Neural network and Fuzzy logic techniques. The framework will further be used to diagnosis and management of Diabetes Mellitus and compare the model with existing work to determine it performance.

KEYWORDS: Diabetes mellitus, Artificial intelligence, expert system, Diagnosis, Genetic algorithm

1. INTRODUCTION

Diabetes Mellitus is a pandemic in both developed and developing countries. It was estimated that 175 million people were living with diabetes mellitus worldwide in 2004 and it was projected that by 2030, the estimate of people with diabetes will be 354 million ([A+14]). It was identified that Africa's have the highest number of people living with diabetes, Nigeria (3.0million), South Africa (1.9 million), Ethiopia (1.4 million), and Kenya (769,000) with Nigeria leading the countries follow by South Africa and these are the most populous countries in Africa ([IDF10]). Providing a solution for inadequate medical services using the education of human resources requires long time and high expenses that may result in increasing the rate of morbidity of patients.

For instance, Artificial Intelligence (AI) in medicine provided numerous advantages in diagnosis, management and prediction of highly complicated and uncertain diseases. Despite the fact that these fields still characterized with high rate of uncertainty and complexity, the use of intelligent systems such as fuzzy logic (FL), artificial neural network (ANN) and genetic algorithm (GA) have been developed in order to improve health care, minimize treatment expenses and improve the quality of life ([Lin9]; [M+01]). While, the main branch of artificial intelligence programs is expert systems which are highly distinguished in a specific field. A new category of systems is the Hybrid intelligent system which relies on the AI techniques, such as expert system, fuzzy logic, neural network and genetic algorithms ([Sma05]).

Using single techniques in diagnosis of diabetes has been comprehensively investigated showing some level of accuracy. Researchers have investigated the effect of hybridizing more than one technique to show enhance results in the diagnosis of diabetes. However, using the combination of two or more technique to identify a suitable treatment for diagnosis of diabetes patients has received less attention ([S+14]). Hence there is need to research in to diabetes diagnosis and management to discover if using the combination of two or more techniques to diabetes diagnosis and management data can provide a better performance in terms of classification accuracy, Receiver Operating Characteristics (ROC), specificity, sensitivity and error rate.

In this work, three intelligent approaches are used to develop the expert system: Genetic, Neural network and Fuzzy logic techniques for diagnosis of DM. The main reason for combining these approaches is to overcome the weakness in one approach while applying it and bringing out the strength of other approaches to find an optimal solution by combining the three intelligent approaches. It will describe the current status of neural networks and fuzzy systems in the diagnoses and management of diabetes. This system will help people to diagnose if they are suffering from diabetes based on identified symptoms.

The main aim of this study is to design a framework for the development of a Genetic-Neuro-Fuzzy Inferential system for diagnosis and management of DM. However, the objectives are to: (i) develop an enhanced hybrid model for diagnosis of DM; (ii) implement the enhanced hybrid system using Java programming Language; (iii) evaluate the performance of the designed enhanced hybrid model; and (v) make a comparison of the enhanced model with existing model for diagnosis of DM.

2. LITERATURE SURVEY

Over the years, various intelligent system techniques have been applied to diagnose and predict diabetes and its complications. Most of these works reported employs used AI (i.e. Expert system, Fuzzy logic, Artificial Neural Networks, and Genetic algorithm or mixed of these techniques between the previous ones. For instance, ([KD11]) proposed fuzzy logic expert system. Triangular membership functions with Madani's inference are used in fuzzy verdict mechanism. Defuzzification was used to convert the fuzzy values into crisp values. The mechanism was used to execute rules and make a decision on the possibility of individuals suffering from diabetes and to present the knowledge with descriptions. The results of the experiment indicated that the system can be used to analyze data and further transfer the acquired information into the knowledge to simulate the thinking process of medical personnel ([OSA17]).
([AOA11]) forecasting diabetic mellitus using ANN. Learning and testing of 768 patients data was tested using the back-propagation algorithm and 268 patients are diagnosed with diabetes. The data was trained to adjust the weights to reduce the error measured between the desired output and the actual output, which stops when it reaches a sufficiently low value. To ANN toolbox in MATLAB was used to analyze the data. Eight inputs and four outputs were tested and compared the results in terms of error. The result obtained will provide solutions to the physician personnel to determine the existence of diabetes in a patient, which is much easier rather than doing a blood test.
([KD11]) classifier diabetic retinopathy in fundus images by developed an automated classifier system. The authors used Adaptive Neuro-Fuzzy Inference System (ANFIS) to differentiate between normal and non-proliferative eyes. ANFIS was trained using the least squares with combinations of Back propagation. The system provided best classification system that can be used as screening tool to analyze and diagnosis retinal images. ([Har10]) used new method to diagnose diabetes disease. The author used principal component analysis (PCA) with (ANFIS), the expert system improve the diagnostic accuracy of the disease. The approach has two stages. The 8 features is reduced to 4 features using PCA in the first stage. The ANFIS was used in diagnosis of diabetes disease as system classifier in the second stage. The proposed system recorded 89.4% classification accuracy.
([TS15]) adopted a fuzzy logic expert system to classifier the Pima Indian Diabetes this was done to improve classification accuracy. The authors used a hybrid system that consists of two AI, (i.e. fuzzy logic and artificial neural network). The Fuzzy neural network (FNN) trained using a back propagation algorithm. Age and blood pressure was used as inputs by divided it into two fuzzy-like; the rest were used as crisp data. The first stage of the proposed model is standardizing the crisp input values and feeding them to the first ANN (ANN1).
After fuzzified, their values were send to FNN and the result is defuzzified. Then obtained results of ANN1 and FNN are used in the second ANN (ANN2) to compute the ultimate output. If the obtained output value is different from the tangible value, the process will be repeated until satisfactory results are reached by change the weights of the networks. The evaluation of the system was measured using k-fold validation and an accuracy of 84.24% is recorded. The proposed hybrid intelligent system used the fuzzy expert system in addition to the neural network based. The inputs have separated into a couple of groups: fuzzy such as blood pressure and medical tests and rest are deemed to be crisp data. Fuzzy system is applied to integrate the fuzzy inputs then feeding them to ANN together with the crisp inputs. ANN has been used for the prediction of DM.

3. PROPOSED GENETIC-NEURO-FUZZY SYSTEM

This section presents design of the system's architecture and procedures performed by each component of the architecture during diagnosis. Components of the architecture are presented in the database, Neuro-Fuzzy-Genetic Inference Engine, and Decision Support Engine. The database serves as a storage location where symptoms of the patient is keyed into the system and based on the weights of the symptoms are stored. The knowledge based of the system is divided into two components (i.e. inference engine) namely a scheduler and an interpreter; for scheduling the rules to be fired and fires the rules using forward chain respectively. It applies Neuro-Fuzzy-Genetic rules to make decision on diseases.

3.1 Neural Network (NN)

Neural Network has the capability of capturing domain knowledge from available indicators and capable of handling both continuous and discrete data. Neural network is used to train and test the designed fuzzy system this was done to improve the performance of the overall system. The Neural network component is made up of variables that consists the diabetes symptoms of patients. Each diagnosis variable has a weight Wi which shows its contribution in the diagnosis process. The raw information obtained from patients is fed into NN via input layer and participation of each category of variables is determined at a hidden layer of the network using:

$$CAT_i = \sum_i^n A_i * W_{Ai} \qquad (1)$$

Where CATi is ith category of variable, n is number of variables in CATi, and Ai is the ith diagnosis variable with weight WAi. Result of the output layer represents the total output of diagnosis by Neural Network component of the architecture. The output result is illustrated in equation (2)

$$Output_{Neural\ Network} = \sum_i^n CAT_i * W_{CATi} \qquad (2)$$

Where WCATi is the connection weight of CATi.

3.2 FUZZY LOGIC

Fuzzy logic used a superset conventional Boolean logic, which have the capability of handling imprecise (vague) and incomplete data that associated with medical records. It resembles human decision making with its ability to work from approximate reasoning and ultimately find a precise solution to a given problem. The process of diagnosis and management of diabetes by the fuzzy logic involves the following stages:

- The input variables such as sign, symptoms and laboratory test results (Fuzzification).
- Building of fuzzy rule base.
- The inference engine (decision making logic of the fuzzy logic component).
- The inference engine output changed into crisp values (Defuzzification).

3.2.1 Algorithm for Fuzzy logic

Step 1: Input crisp values of glucose, INS, BMI, DPF and age.
Step 2: Set the triangular membership function for the fuzzy number.
Step 3: Build the fuzzy numbers for glucose, INS, BMI, DPF and age for input set & output set
Step 4: Execute Mamdani's Fuzzy inference method.
Step 5: Input the rules and calculate the matching degree of rule with "OR" fuzzy disjunction for fuzzy input set (Glucoselow, Glucosemedium, Glucosehigh, INSlow, INSmedium, INShigh, BMIlow, BMImedium, BMIhigh, DPFlow, DPFmedium, DPFhigh, Ageyoung, Agemedium, Ageold).
Step 6: Compute the aggregation of the fired rules for fuzzy output set DM (DMverylow, DMlow, DMmedium, DMhigh, DMveryhigh).
Step 7: Defuzzify into the crisp values by:

$$z^* = \frac{\int \mu A(z).zdz}{\int \mu A(z)dz} \qquad (3)$$

Where, ∫ denotes algebraic integration, μA(z) means the number of fuzzy numbers of the output fuzzy variable DM and z represents the weight for μA(z).
Step 8: Represent the knowledge in human language form.
End.

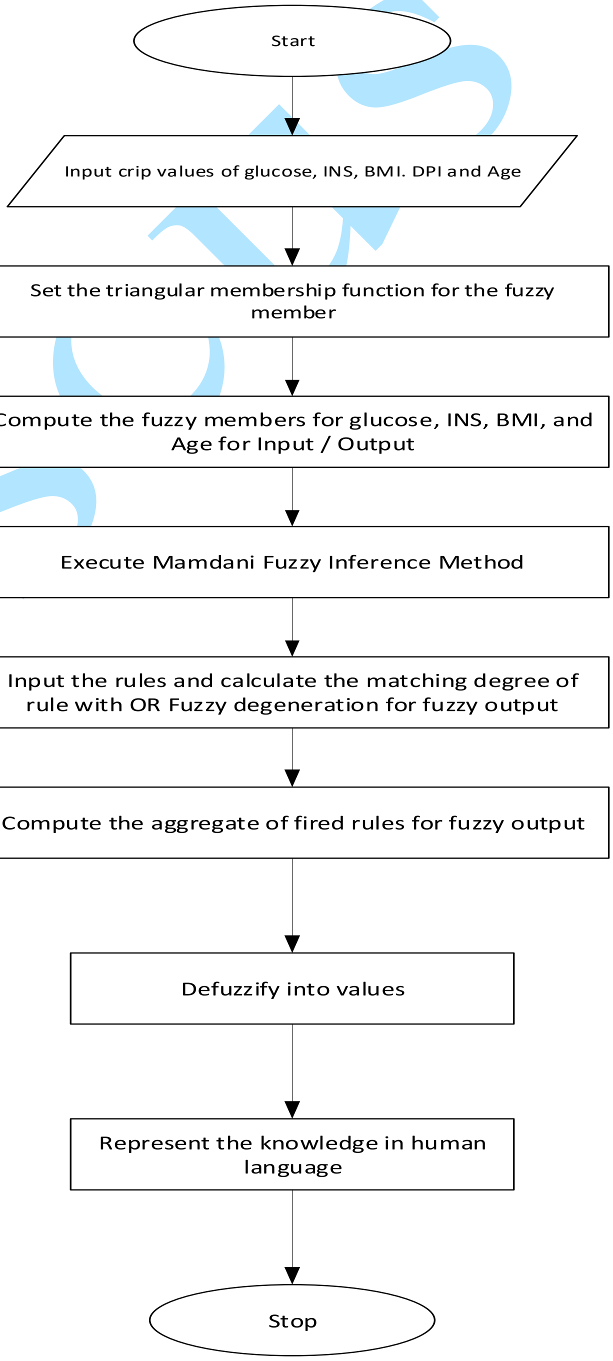

Figure 1: Fuzzy Logic Flowchart

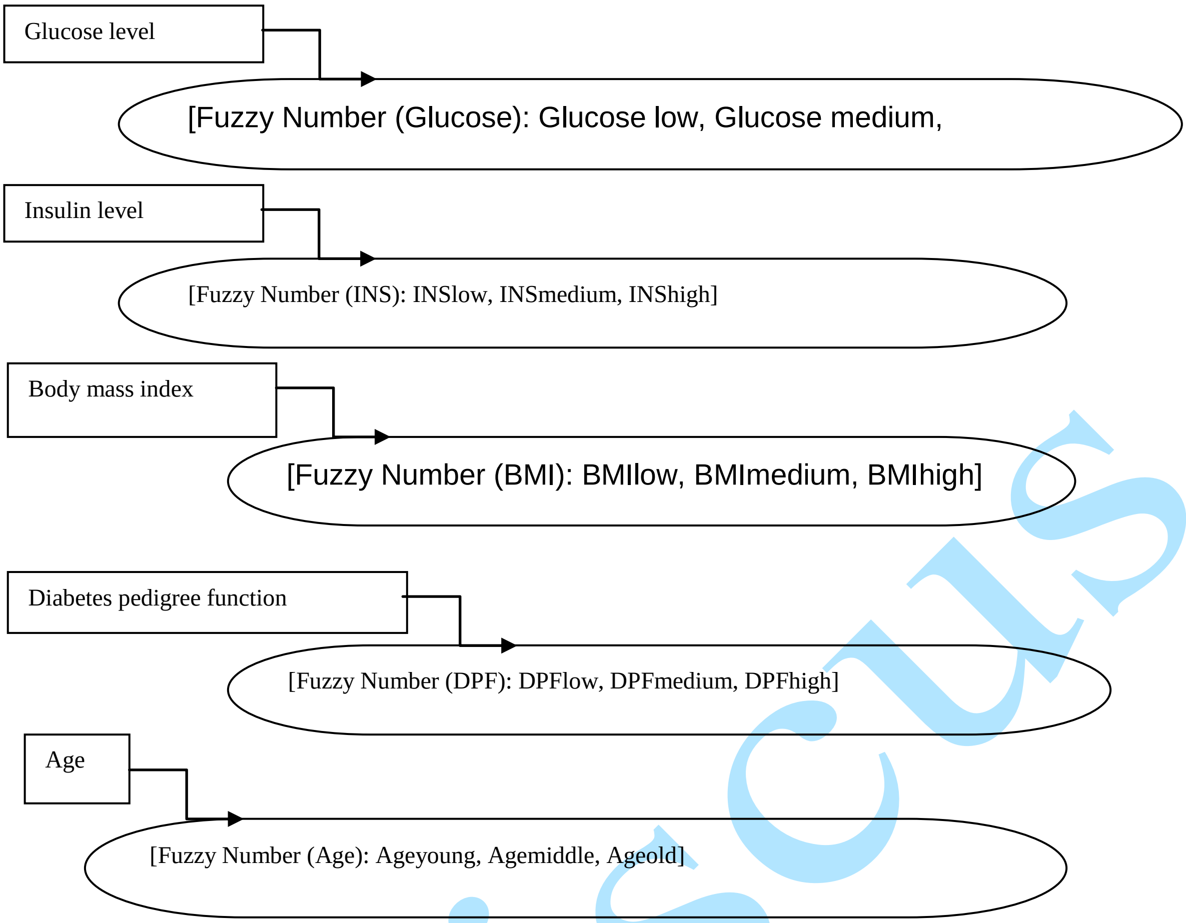

Figure 2: Sentence Analysis represents the physical data of the person

(a) FUZZIFICATION

This is the first step of fuzzy inference system. It's involves a domain transformation where crisp inputs are transformed into fuzzy inputs. The fuzzy sets for the indicators, and the output of diagnosis and management of diabetes along with the membership function were defined in fuzzification. The Fuzzy Sets for the Indicators and for the Output of Diabetes Mellitus is as follow;

Number of Pregnancy: {Absent, Normal, Risk}.
Diastolic Blood Pressure: {Low, Medium, High, Very High}.
Teiceps Skin Thickness: {Good, Average, Below Average}.
Glucose: {Low, Medium, High}.
Insulin: {Low, Medium, High}.
Body Mass Index (BMI): {Low, Medium, High}.
Diabetes Pedigree Function (DPF): {Low, Medium, High}.
Age: {Young, Medium, Old}.
Output: {Low, Medium, High}.

For the output fuzzy set, the system used 0 = Low, 1 = Medium, and 2= High. The following table 3 shows the ranges of the output fuzzy sets.

Table 1: Ranges of the Output Fuzzy set for Diabetes Mellitus Application

Output Fields	Range	Fuzzy Set
	< 0.4	Low
Result	0.4 – 0.6	Medium
	0.5 – 1	High

For the final result, this study considered low as No Diabetes medium and high as Diabetes. After the indicators and their fuzzy sets have been defined, the range values were prepared for the fuzzy sets of each indicator from the collected data collected of the physicians. When the range values for the fuzzy sets were ready, the equations were constructed by using the range values to generate the membership function. This study applied triangular (4) and trapezoidal (5) membership functions equation.

$$\mu(x) = \begin{cases} 0, x < a \\ \dfrac{x-a}{b-a}, a < x \le b \\ \dfrac{c-x}{c-b}, b < x < c \\ 0, x > a \end{cases} \qquad (4)$$

$$trapezoid(x:a,b,c,d)=\begin{cases} 0, x \le a \\ \dfrac{x-a}{b-a}, a \le x \le b \\ 1, b \le x \le c \\ \dfrac{d-x}{d-c}, c \le x \le d \\ 0, d \le x \end{cases} \quad (5)$$

After generating the membership functions of the fuzzy sets, in order to get the most appropriate membership from the fuzzy set of each indicator, the maximum was taken from the generated membership function of the fuzzy set in each indicator. The maximum was considered because this study followed the Mamdani method to develop the FIS. In Mamdani, maximum is taken from the generated membership function of the fuzzy sets to choose the appropriate membership function.

(b) ESTABLISHMENT OF THE FUZZY RULE BASE

After obtaining the linguistic terms of the indicators, the next step is to generate the fuzzy rules. For this research work, 25 fuzzy rules were developed for diagnosis and management of diabetes mellitus. The rules set are given below.

i. If Glucose is Low then Diabetes Mellitus is Low
ii. If Glucose is Medium then Diabetes Mellitus is Medium
iii. If Glucose is High then Diabetes Mellitus is High
iv. If Insulin is Low then Diabetes Mellitus is Low
v. If Insulin is Medium then Diabetes Mellitus is Medium
vi. If Insulin is High then Diabetes Mellitus is High
vii. If Body Mass Index is Low then Diabetes Mellitus is Low
viii. If Body Mass Index is Medium then Diabetes is Medium Mellitus
ix. If Body Mass Index is High then Diabetes Mellitus is High
x. If Diabetes Pedigree Function is Low then Diabetes is Low
xi. If Diabetes Pedigree Function is Medium then Diabetes Mellitus is Medium
xii. If Diabetes Pedigree Function is High then Diabetes Mellitus is High
xiii. If Age is Young then Diabetes Mellitus is Low
xiv. If Age is Medium then Diabetes Mellitus is Medium
xv. If Age is Old then Diabetes Mellitus is High
xvi. If Number of pregnancy is absent then Diabetes Mellitus is Low
xvii. If Number of pregnancy is Normal then Diabetes Mellitus is Medium
xviii. If Number of pregnancy is High then Diabetes Mellitus is High
xix. If Triceps skin fold thickness is Good then Diabetes Mellitus is Low
xx. If Triceps skin fold thickness is Average then Diabetes Mellitus is Medium
xxi. If Triceps skin fold thickness is Below average then Diabetes Mellitus is High
xxii. If Diastolic blood pressure is low then Diabetes Mellitus is Low
xxiii. If Diastolic blood pressure is Medium then Diabetes Mellitus is Medium
xxiv. If Diastolic blood pressure is High then Diabetes Mellitus is High
xxv. If Diastolic blood pressure is Very high then Diabetes Mellitus is High

(c) BUILDING THE INFERENCE ENGINE.

Inference is the process of drawing conclusion from existing data. The knowledge processor that is modeled after expert's reasoning is inference engine. The membership functions, if-then rules and logical functions are the process of fuzzy inference that are described in them. The following are the five parts of fuzzy inference engine:

i. Fuzzification
ii. The if-then fuzzy operator (AND or OR) in the antecedent
iii. Inference from the predecessor to the resultant
iv. Aggregation of the consequents across the rules
v. Defuzzification

(d) DEFUZZIFICATION

The process of producing a quantifiable result in crisp logic is called defuzzification with a corresponding memberships degrees and a given fuzzy sets. The firing strength of each rule is determined by the last part in the inference engine. Rules 25 and 27 fired at 60% or 0.6 and 40% or 0.4 respectively. For each rule, the logical products must be inferred or combined before being passed on to the defuzzification process (max-min'd, max-dot'd, averaged, root-sum-squared, etc.) for crisp output generation. The inference engine used in this research is presented in Equation 6.

$$RSS = \sqrt{\sum R^2} = \sqrt{(R_1^2 + R_2^2 + R_3^2 +, \dots, R_n^2)} \quad (6)$$

Where RSS is the Root Sum Square formula.
The strength values of different rules where $R_1^2, R_2^2, R_3^2, \dots, R_n^2$ which share the same conclusion.
The effects of applicable rules, computes the "fuzzy" centroid of the composite area and scales the functions at their respective magnitudes were combines by RSS technique. The method is selected

for this work because it gives the best weighted influence to all fire rules, but the method is more complicated mathematically than other methods ([SS03]).

3.3. GENETIC ALGORITHM

In this study, genetic optimization is performed to choose optimal values from a group of diagnostic parameters which serve as input. There are 8 attributes in PIMA Indian diabetes dataset in the ANN but the task is to decide which parameters are taken as input in order to minimize computational complexity. The Darwin's theory of natural selection and 'survival of the fittest is called Genetic Algorithm (GA). The algorithm is used mostly in optimization method for feature selection. A problem that advances over successive iteration (generations) through the process of competition and controlled variation uses GA. The process of selection is used to select the chromosomes in the population, the selection must satisfy the associated fitness to form new ones in the rivalry process. Crossover and mutation are genetic operators used to create the new chromosomes. From the current population, the GA uses three main types of rules at each step to create the next generation:

1. The parents that contribute to the population at the next generation (individual) was select using selection rules.
2. Two parents were combined using crossover rules to form children for the next generation
3. Mutation rules apply random changes to individual parents to form children.

A new population P(t) were produces using selection mechanism with copies of chromosomes in P(t-1). Every copies received by each chromosome depends on its fitness; each with higher fitness have a greater chance of contributing copies to P(t). The operators applied to P(t)are crossover and mutation. Crossover produces two new offspring from two individuals called parents by swapping parts of the parents. The operator exchanging substrings after a randomly selected crossover point. The likelihood of crossover applied depends on probability defined by the crossover rate, a random choice is made. The operator is not always applied to all pairs of chromosomes in the new population. Mutation is used to prevent premature loss of population diversity by randomly sampling new points in the search space. Mutation overturning one or more random bits in the bit string with a probability equal to the mutation rate. Termination may be triggered by finding an acceptable solution by some criterion or reaching a maximum number of generations. An individual chromosome consists of 24 genes and each gene represents the connection weight of a diagnosis variable in a length of 1 bit. One feasible solution is to generate an initial population holding a set of possible solutions from random chromosomes. A chromosome is represented as a vector C = (CA, . . . , CX) of binary decision variables Ci=0,2,3; encoded in binary representation as string consisting {0, 1} genes. A gene Ci =1 if the ith variable is included in a solution set of a diagnostic process otherwise 0. Fitness function is used to optimize each chromosome by evaluating the genes that constitute the chromosome using their fitness value.

As evolutionary algorithm continues through its cycle, fitness value of each chromosome keeps improving till it reaches an optimum value when it can no longer improve. A number of constraints have been considered in carrying out appropriate management of disease in medical diagnosis; therefore fitness evaluation of chromosome must be done with proper constraint validation. Constraints can be termed as objectives that must be achieved in which some render most of the solutions from the search space hence; its application in GA is problem specific. The fitness evaluation of an individual F(i) is done as:

$$F_i = \left(1 + \sum_i^n W_i * C_{i(p)}\right)^{-1} \qquad (7)$$

where n is the number of diagnosis variables, Wi is the weight associated with ith variable and Ci(p) is the number of violations for ith constraint at solution p. This fitness function has a range of [0, 1] and an optimal solution occurs when we have 0 violations thus $\sum_{i=0}^{n} W_i * C_{i(p)}$ which results in Fi = 1. Chromosomes with higher fitness value are selected as parents for mating in order to produce outstanding candidates and maximize the fitness function. The probability of choosing an individual for genetic operation is proportional to its fitness, that is, if the fitness value of an individual is Fi, then the probability, Pi, of choosing the individual is:

$$P_i = \frac{F_i}{\sum_{i=0}^{n-1} F_i} \qquad (8)$$

This process is repeated until an optimal connection weight is achieved.

3.4. NEURO-FUZZY- GENETIC INFERENCE SYSTEM (NFGEIS)

NFGEIS is an inferential technique proposed to integrate GA, ANN and FL components in order to provide a self-learning and adaptive system for handling uncertain and imprecise data for diagnosis of diabetes. The inference system hires feed forward propagation with nine layers of neurons as learning technique. Where computations take place, both hidden and output layers consist of active nodes and the nodes at input layer are passive. The inference engine consists of reasoning algorithm driven by the production rules based on Mamdani's Inference Mechanism. Of the seven layers, the first one consists of active nodes which denote inputs to the system. The inputs are numeric values representing how severe a patient feels the diagnosis variables. The output of this layer is the linguistic labels corresponding to each input value.

The second layer is made up of adaptive nodes that receive the output of preceding layer as input, and produce their corresponding membership grade determined as:

$$L_2(x_i) = \mu_{Ai}(X_i) \quad (9)$$

The fuzzy value of each variable is computed using triangular MF, given as:

$$\mu_{Ai}(X_i) = \frac{x_i - b}{a - b} \quad (10)$$

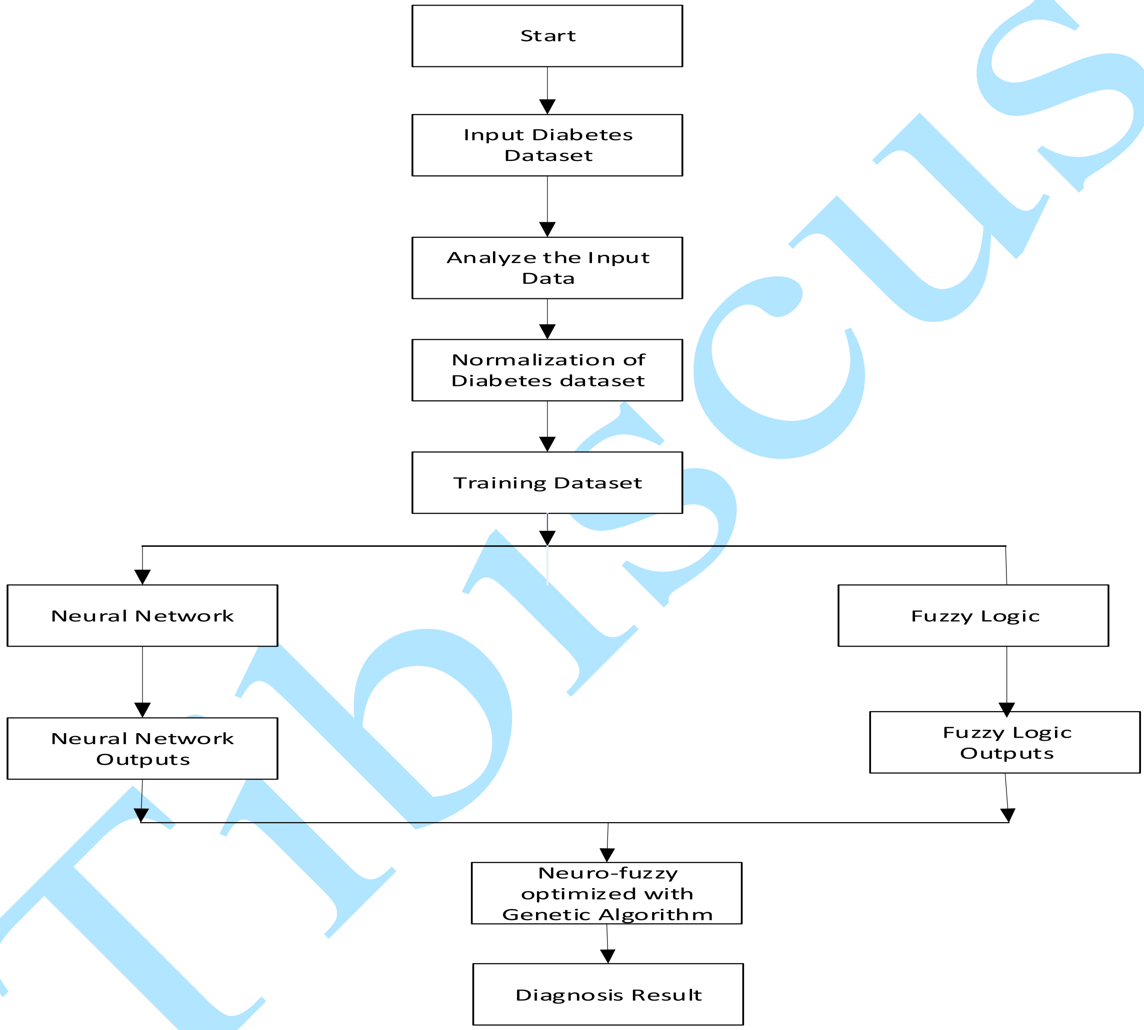

Figure 3: Block Diagram for the Proposed System

4. CONCLUSION

The ubiquitousness of information technology has seen medical healthcare delivery systems becoming progressively more integrated, coordinated, effective and efficient through computerization platforms such as artificial intelligence and experts systems as well as decision support systems. Developing countries are increasing suffering from diabetes, the ever increase population can be described as epidemic. In 2005 more than 246 million patients worldwide were being treated for this chronic disease from International Diabetes Foundation. According to International Diabetes Foundation reports by the year 2025 over 300 million people worldwide will have diabetes. Epidemiological investigations shown that the actual number of people with diabetes mellitus is definitely higher since, on each diagnosed patient there is always one non-diagnosed patient (Diabetes Foundation, 2005). A high percentage of patients with diabetes belong to the group of active population. In this paper a framework model was developed for diagnosis and management of diabetes mellitus. Researchers have used different model and algorithms to diagnose, predict and manage of diabetes mellitus. The model will be used to diagnose diabetes and evaluation of the model with existing algorithms would be carried out.

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