An Improved Hybridization in the Diagnosis of Diabetes Mellitus Using Selected Computational Intelligence

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Abstract. Artificial Intelligence (AI) in medicine has provided numerous advantages in diagnosis, management, and prediction of highly complicated and uncertain diseases like diabetes. Despite the high rate of complexity and uncertainty in this area, computational intelligent systems such as the Artificial Neural Network (ANN), Fuzzy Logic (FL) and Genetic Algorithm (GA) have been used to enhance healthcare services, reduce medical costs and improve quality of life. Hence, Computational Intelligence Techniques (CIT) has been successfully employed in diabetes disease diagnosis, risk evaluation, patient monitoring, and prediction in the medical field. Using single technique in the diagnosis of diabetes has been comprehensively investigated showing some level of accuracy, but the use of hybridized can still perform better. Diabetes Mellitus (DM) is one of contemporary society's most chronic and crippling diseases and poses not just a medical issue but also a socio-economic issue. Therefore, the paper develops an improved hybrid system for the diagnosis of diabetes mellitus using FL, ANN, and Genetic Algorithm (GA). FL and ANN was combined for the diagnosis of diabetes mellitus and GA is used for features selection and optimization. The result performed better during the diagnosis process for diabetes mellitus. Hence the results of the comparison showed that Genetic-Neuro-Fuzzy Inferential System (GNFIS) had a better performance with 99.34% accuracy on the whole dataset used when compared with FL and ANN with 96.14% and 95.14% respectively. The proposed system can be used in assisting medical practitioners in diagnose diabetes mellitus and increase its accuracy

Keywords: Diabetes mellitus · Fuzzy logic · Artificial neural network · Genetic algorithm · Computational intelligence technique

1 Introduction

Diabetes is increasing rapidly in developed countries; the increase is widespread because over 246 million people worldwide were treated from this chronic disease according to data from the International Diabetes Foundation in 2005. It was also reported that by 2025 at least 300 million people worldwide may develop diabetes disease [1]. The exact

number of people with diabetes mellitus is higher since, by a definite epidemiological study on each diagnosed patient, there is one non-diagnosed patient. [2]. A large number of patients with diabetes belong to the group of the working population.

According to the International Diabetes Foundation, 2010 Nigeria is one of Africa's most populous countries with the largest number of people with diabetes, with 3.0 million, 1.9 million South Africans, 1.4 million Ethiopians, and 769,000 Kenyans. Providing a remedy for insufficient medical care using human resource education involves long and high costs which can result in an improved patient morbidity rate.

Meanwhile, emphasis on the need for preventive methods has been the interest of health care, researchers, and medical personnel around the world [3–5]. The preventive method that would support the well-planned assessment that could moderate or lower the risk of transitioning from pre-diabetes to diabetes. Diabetes mellitus is graded as "type 1," "type 2," "gestational diabetes" and other different forms of [6].

Diabetes Mellitus represents both the medical and socio-economic problems in modern society [7–10]. In developed and developing countries the disease is widespread. It was estimated that 175 million people having diabetes in 2004, worldwide and it was projected that an estimate of 354 million will have diabetes by 2030 [11]. According to the International Diabetes Foundation, 2010, Nigeria is one of the most known countries in Africa that records the huge figure of DM, three million in South Africa, one million and nine hundred thousand in Ethiopia, and one million and four hundred thousand in Kenya 769,000 [12]. Providing a solution for inadequate medical services using the education of human resources requires a long time and high expenses that may result in an increased morbidity rate in patients [13, 27].

Artificial Intelligence (AI) in medicine has provided numerous advantages in diagnosis, management, and prediction of highly complicated and uncertain diseases [14, 15]. Despite the high rate of complexity and uncertainty in this field, computational intelligent systems like NN, FL, and genetic algorithm (GA) have been used to improve health care, minimize treatment expenses and improve the quality of life [16–18]. A new system category is the hybrid intelligent system focused on artificial intelligence techniques such as fuzzy logic, neural network, expert system, and genetic algorithms [19, 20].

Using single technique in the diagnosis of diabetes has been comprehensively investigated showing some level of accuracy [12, 21]. Researchers have investigated the effect of hybridizing more than one techniques to show better results in the diagnosis of diabetes [22] but to the best of our knowledge none use GA for features selection. Therefore, the work developed an improved neuro-fuzzy inferential system that combines NN and FL and used GA for the optimization of parameters before the classification of DM.

2   Related Work

Different types of intelligent system techniques have been applied to detect, classify, and diagnose diabetes and its complications. Expert System (ES) is built using one or combination of these techniques: Artificial Neural Networks (ANN), Genetic Algorithm (GA), Fuzzy Logic (FL) [23] used fuzzy logic to build an expert diabetes diagnostics program with judgment mechanism for instance. Triangular membership functions with

Mamdani's inference are used in a fuzzy verdict mechanism. The conversion of fuzzy values into crisp values was done with the Defuzzification method. The judgment process was used to enforce rules to make a decision about the probability of diabetes sufferers and to present the information with descriptions. The experimental result shows that the expert system can pass the information acquired into the expertise to replicate the human thought process and can analyze data from the database [24].

[25] used an adaptive neuro-fuzzy inference system (ANFIS) and principal component analysis (PCA) for diabetes diagnosis to improve the diagnostic accuracy of diabetes. He divided the system into two stages, the first stage of 8 features dataset is reduced to 4 features by PCA and in stage two the reduced dataset was used to diagnose patients with diabetes disease using the designed system classifier (adaptive neuro-fuzzy inference system). The proposed system recorded 89.47% classification accuracy.

[26] proposed a fuzzy logic expert system to improve on Pima diabetes dataset classification accuracy. Artificial neural network (ANN) with two neural networks were combined to form a hybrid system, a back propagation algorithm was used to train the proposed system. Fuzzy like age, blood pressure, and the rest were used as crisp data after dividing the inputs into two groups. The standardized crisp input values are fed to the first ANN in the first stage (ANN1) and the result of the defuzzyfied from fuzzing fuzzy data and their values are presented to FNN. To calculate the final output, the results from ANN1 and FNN were fed to the second ANN (ANN2). If the output value is different from the actual value, the weights of these networks will change, and the process was repeated until reasonable results are reached. The developed system was tested using K-fold cross-validation and achieved an accuracy of 84.24%.

The hybridized intelligent system used the fuzzy expert system in addition to the neural network base. The inputs have been separated into a couple of groups: fuzzy such as blood pressure and medical tests and rest are deemed to be crisp data. A 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. This paper tends to add GA for features selection before applying ANN and FL.

3   An Overview of the Techniques

3.1   Brief Description of Some Computational Intelligence Techniques Used

Neural Network (NN)
Neural networks can easily handle both continuous and discrete data and can gather data from available indicators. A neural network has been used to train and test the designed Fuzzy system, as well as to develop the per-for-mance of the overall system. This consists of 8 features, namely: diastolic blood pressure, 2 h of oral glucose tolerance test (plasma glucose concentration), some pregnant days, skin folding thickness of Triceps, 2-h serum insulin (INS), body mass index (BMI), diabetes pedigree function (DPF), and sex. Wi has been used to show that that attribute has a weight that contributes to the process of diagnosis. The attributes of patient diagnosis were fed into the neural network as input

layer and contribution was calculated at the hidden layer of each group of variables. The equation used is as follows:

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

Fuzzy logic has the power of handling imprecise and imperfect data which is one of the characteristics of medical records, and it is a superset of traditional Boolean. This seeks a definite solution to a given problem and often parallels human decision-making in its ability to function from indirect reasoning. The steps involved in diagnosing and controlling diabetes through fuzzy logic are the following process:

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

Where WCATi is the connection weight of CATi

Fuzzy Logic
Fuzzy logic has the strength of handling imprecise and incomplete data that is one of the characteristics of medical records, and it is a superset of the conventional Boolean. It finds a precise solution to a given problem and its ability to work from approximate reasoning also resembles human decision making. The following process is the stages involves in diagnosis and management of diabetes by fuzzy logic:

1. Fuzzification of the attributes input by the patient
2. Formation of a fuzzy rule base system.
3. Inference engine: the building of decision making for the fuzzy logic component.
4. Defuzzification of the output results from the inference engine into crisp values.

Algorithm for Fuzzy Logic
Phase 1: Glucose, INS, BMI, DPF, and age were used as crisp values for the data.
Phase 2: Set the Fuzzy Number triangular membership function.
Phase 3: Construct the Fuzzy numbers for the input set & output set of the five (5) attributes
Phase 4: Mamdani was used for executing a fuzzy inference process.
Phase 5: Enter the rules and measure the corresponding degree of law for the fuzzy input collection "OR" disjunction (Glucoselow, Glucosemedium, Glucosehigh, INSlow, INSmedium, INShigh, BMIlow, BMImedium, BMIhigh, DPFlow, DPFmedium, DPFhigh, Ageyoung, Age-old).
Phase 6: Calculate the aggregation of the fuzzy output set DM fired rules (DMverylow, DMlow, DMmedium, DMhigh, DMveryhigh).
Phase 7: Defuzzify into the crisp values by:

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

Where $\int$ is the algebraic integration, $\mu A(z)$ is the number of fuzzy numbers of the fuzzy DM output variable and z is the weight of $\mu A(z)$. Step 8: Reflect the type of information in the human language.

Fuzzification

Fuzzification is the first step in the Fuzzy Inference method. It's a domain transformation that transforms crisp inputs into fuzzy inputs. In fuzzification, the fuzzy sets for the indicators, and the performance of diagnosis and diabetes management along with membership function were established.

Table 1. Ranges of the output fuzzy set for diabetes mellitus application

Output fields	Range	Fuzzy set
Result	<0.4	Low
	0.4–0.6	Medium
	0.61–1	High

The Fuzzy Sets for the Indicators and the Output of Diabetes Mellitus is as follow;

Number of Pregnancy: {Absent, Normal, Risk}.
Diastolic Blood Pressure: {Low, Medium, High, Very High}.
Triceps 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:

For the final result, this study considered low as No Diabetes, medium, and high as Diabetes. After identifying the indicators and their fuzzy sets, the range values for each indicator's fuzzy sets were prepared, and the evaluation for the data used for the model was performed by the doctors. Once the range values for the fuzzy sets were ready, the equations were built to produce the membership function using the range values. Triangular, trapezoidal, and bell-shaped membership functions are some of the types of membership functions that have been proposed. In this work, triangular membership function was used because calculations with triangular membership are easy, and shapes are simpler and more versatile and have fewer complexes when comparing

other membership functions when dividing values (low, mid, and high MF). In Eq. 3.4 the triangular component function is seen.

$$0 \begin{cases} 0, \ x < a \\ \frac{x-a}{x-b} \ a < x \le b \\ \frac{c-x}{c-b} \ b < x < c \\ 0, \ x > a \end{cases} \text{Triangular membership functions} \tag{4}$$

After generating the membership functions of the fuzzy sets, 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, the maximum is taken from the generated membership function of the fuzzy sets to choose the appropriate membership function.

3.2 Genetic Algorithm

Genetic algorithms have been used to select optimal attributes (values) from the diagnostic parameters that serve as input, as well as device optimization. Indian diabetes dataset PIMA has eight attributes. In Neural Network, a genetic algorithm was used to choose which attributes to be used as input to reduce the complexity of computation.

3.3 Genetic-Neuro-Fuzzy Inference System (GNFIS)

The proposed approach incorporates ANN, Fuzzy logic, and Genetic Algorithm to construct an inferential system called the Genetic-Neuro-Fuzzy Inference System (GNFIS), designed to handle ambiguous and imprecise diabetes diagnostic data, self-learning, and adaptive system. To construct the inference method, the feed-forward propagation learning technique composed of nine layers of neurons was employed. Both secret and output layers consist of active nodes, which are inactive nodes at the input layer where computations occur. The reasoning algorithm based inference engine used Mamdani's Inference Mechanism which is a law of development. The active nodes represent inputs from computers and are one of seven layers. Numeric values are used as variables for the diagnosis to reflect how bad a patient is feeling. For every input tag, the output layer is the corresponding linguistic labels.

Using the formula below, the second layer composed of adaptive nodes was used to obtain the output of the preceding layer as input and generated their corresponding membership grade:

$$L_2(x_i) = \mu_{Ai}(X_i) \tag{5}$$

Increasing variable's Fuzzy value is calculated using triangular MF, given as:

$$(X_i) = \frac{x_i - b}{a - b} \tag{6}$$

4   Methodology

4.1   Model Diagram

A Block diagram of the theoretical model for diabetes diagnosis is shown in Fig. 1 below; it demonstrates the flow of a diabetic Mellitus diagnostic model.
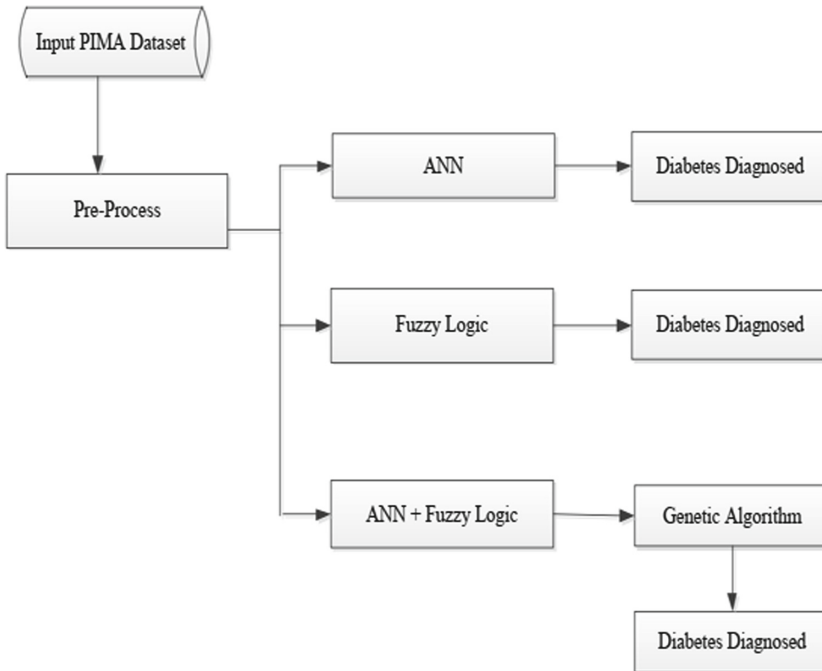

Fig. 1. Block diagram for the proposed system model

4.2   Data Used for the System

In this work, the direct rating method was used for acquiring data, which is an effective way of constructing a membership function and direct means of collecting data. Also, to rate the membership function, all the rating indicators (subject) in sequences of data were presented (objects) to the domain experts. To construct a membership function, the responses of several physicians were collected. Both lowest and highest values were used finally to form the ranges for membership function calculation. Minimum values are the lowest and highest as the maximum values. The data used fell within the range, removing any chance of losing data. Table 2 shows the ratings of the data for the proposed system for diagnoses of diabetes mellitus.

Table 2. Results of rating for the indicators of the diabetes mellitus by physicians

Input field	Range				Fuzzy set
	1st Physician	2nd Physician	3rd Physician	4th Physician	
1. Glucose	$\leq$71–110	$\leq$90	$\leq$120	$\leq$121	Low
	94–120	95–130	97–138	96–145	Medium
	$\geq$121	$\geq$122	$\geq$124	$\geq$125	High
2. INS	$\leq$15–80	$\leq$15–78	$\leq$20–86	$\leq$17–87	Low
	15–100	20–150	17–90	15–100	Medium
	$\geq$89–194	$\geq$95–193	$\geq$192	$\geq$194	High
3. BMI	$\leq$24	$\leq$27	$\leq$33	$\leq$30	Low
	24	35	39	40	Medium
	$\geq$33	$\geq$35	$\geq$37	$\geq$40	High
4. DPF	$\leq$0	$\leq$0.2	$\leq$0.3	$\leq$0.4	Low
	0.2	0.3	0.4	0.6	Medium
	$\geq$0.4	$\geq$0.6	$\geq$0.7	$\geq$0.4	High
5. Age	$\leq$30	$\leq$29	$\leq$38	$\leq$35	Young
	33	40	42	43	Mid
	$\geq$45–55	$\geq$47–54	$\geq$50	$\geq$58	Old

Indicators of Diabetes Mellitus

i. **Pregnancy number:** This is graded as absent, weak, and risky. If a person is male then there will be no pregnancy number.

ii. **Diastolic blood pressure:** This field has four fuzzy sets low, medium, high, and very high.

iii. **Triceps skinfold thickness:** It a measurement factor used for body fat.

iv. **Glucose:** Glucose or blood sugar is the principal source of energy in the blood. It is measured by a 2-h glucose concentration after 2 h of having breakfast (American Diabetes Association, 2014). Glucose has three low, medium, and high Fuzzy sets.

v. **Insulin (INS):** Insulin is the hormone that the pancreas excretes to help transfer glucose from the blood into the cells that are used for energy. It is measured by 2-h serum insulin (INS) after 2 h of having breakfast (American Diabetes Association, 2014). If insulin is not responded well by the cells, then glucose cannot enter the cells. As a result, the cells lack the fuel they need, and glucose builds up in the bloodstream. INS has three low, medium, and high Fuzzy sets.

vi. **Body Mass Index (BMI):** BMI is used as a measure of the body's weight to a person's height. This area consists of three small, medium, and high Fuzzy sets in the developed system.

vii. **Diabetes Pedigree Function (DPF):** DPF is the statistical classification of a certain data category (American Diabetes Association 2014). For example, of the age group 40–45, data are analyzed and calculated when determining statistical values for the age group. DPF consists of three fuzzy sets low, medium, and high.

viii. **Age:** Age is considered a further diabetes predictor. Age has three new, medium, and old Fuzzy collections.

5   Result and Discussion

The program has been developed to diagnose Mellitus Diabetes. The program was developed and using the Pima Indian Diabetes Database (PIDD) dataset to test the performance of the proposed system. The database has 8 input attributes, and the third as goal variable. The following are the attributes of PIDD database namely: Triceps skinfold thickness (mm), number of times pregnant, 2-H serum insulin (mu U/ml), diastolic blood pressure (mm Hg), diabetes pedigree size, body mass index (weight in kg/(height in m) ^2), 2-h oral glucose tolerance test plasma glucose concentration, and age (years). The attributes were used to test if a patient is tested-positive or tested-negative. The totals of 768 patients are available in PIDD.

100 patients were used for training test from the Pima database diabetes dataset and stored as rules in the database (patient medical records) to assess the efficiency of the built program. To get a simple estimate 100 patients were used to check the proposed program from the dataset. Human respiratory disease experts assess the production value of each rule from the documents that were obtained for the program. Human knowledge is used to determine the sensitivity of the input variables. The severity of each variable reflects their contribution to the disease of diabetes.

Java programming language was chosen to build the system this is because it is a high-level programming language and object-oriented based program with functions and class which could be used to develop and link a graphic user interface for user interaction and responsiveness. The diagnostic system employed several components in JavaScript to achieve the implementation of this system.

5.1   Performance Evaluation Metrics

Basic assessment criteria and evaluation focused based on classification accuracy using True Negative (TN), True Positive (TP), False Negative (FN), and False Positive (FP). Table 3 displayed the performance evaluation metrics used in the paper.

Where:

TN = the number of healthy people among those diagnosed with diabetes
TP = means the number of people who currently have diabetes among those who have been diagnosed as diabetic
FN = number of people who were diagnosed as diabetic found to be stable
FP = depicts the number of unhealthy individuals, i.e. diabetic, but diagnosed as well.

Table 3. Performance evaluation metrics

Measures	Definition	Formula
Sensitivity test	Measure the ability to correctly detect diabetes disease	$TP/(TP + FN)$
Specificity test	Measure the ability to avoid calling normal things as diabetes disease in medical tests	$TN/(TN + FP)$
PPV	Positively predicated value	$TP/(TP + FP)$
NPV	Negatively predicated value	$TN/(TN + FN)$
Accuracy	Measure the percentage of correctly detect diabetes disease	$\frac{TN+TP}{TN+FP+FN+TP} \times 100$

5.2 Genetic Neuro-Fuzzy Inference Diagnostic System Experimental Results

The results gathered from the developed GNFIS diagnostics system for Diabetes Mellitus are shown in the following sections.

The Experimental Results of the GNFIS
Fifty (50) specimens were chosen for test runs from the sample. To evaluate the different output metrics the one trail/run closer to the average classification accuracy value was selected. The overall accuracy of the results rating was 97.79%. The GNFIS system performance assessment metrics for classifying the reduced dataset are shown in Table 2 and Table 3; this demonstrates that the developed system's classification accuracy is better than the current research.

Genetic algorithm (GA) was used to delete samples and cases that were outliers, noisy, and inconsistent, with missing values being replaced by mean. Using a 10-fold cross-validation technique for classification, the algorithm was used as a feature selection method, and its output was fed to NFIS. During each run, GA was used to select different features from the original collection of attributes, and their classification accuracy for each run was registered. To obtain the satisfactory result the experiment was replicated 50 times. Table 4 and Fig. 2 shown the evaluation metrics obtained from the proposed system.

Table 4. Evaluation metrics obtained from GNFIS diagnosis

Performance measures	Reduced dataset
No. of attributes used	**5**
Sensitivity (%)	96.00
Specificity (%)	99.00
Positively predicted value (%)	99.00
Negatively predicted value (%)	98.00
GNFIS accuracy (%)	98.00

Table 5. The accuracy obtained from the three systems for diagnosis

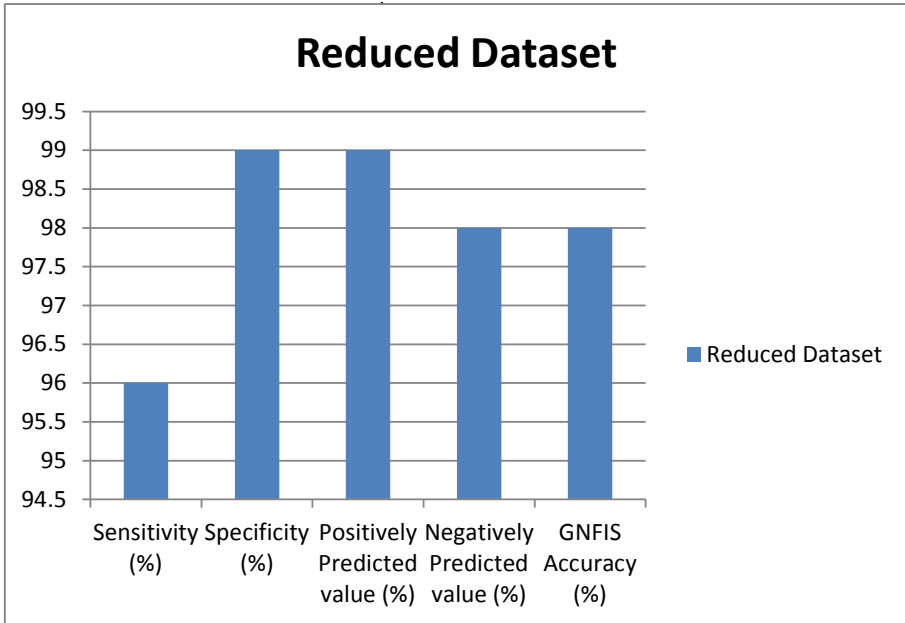| Performance measures	Reduced dataset
No. of attributes used	5
Fuzzy logic accuracy (%)	97.00
ANN accuracy (%)	96.00
GNFIS accuracy (%)	99.00

Fig. 2. Graphical representation of evaluation metrics for GNFIS

The accuracy obtained from the system for diabetes mellitus diagnosis is displayed in Table 5 and Fig. 3. The results show that the hybridized system performed better compared with the single technique.
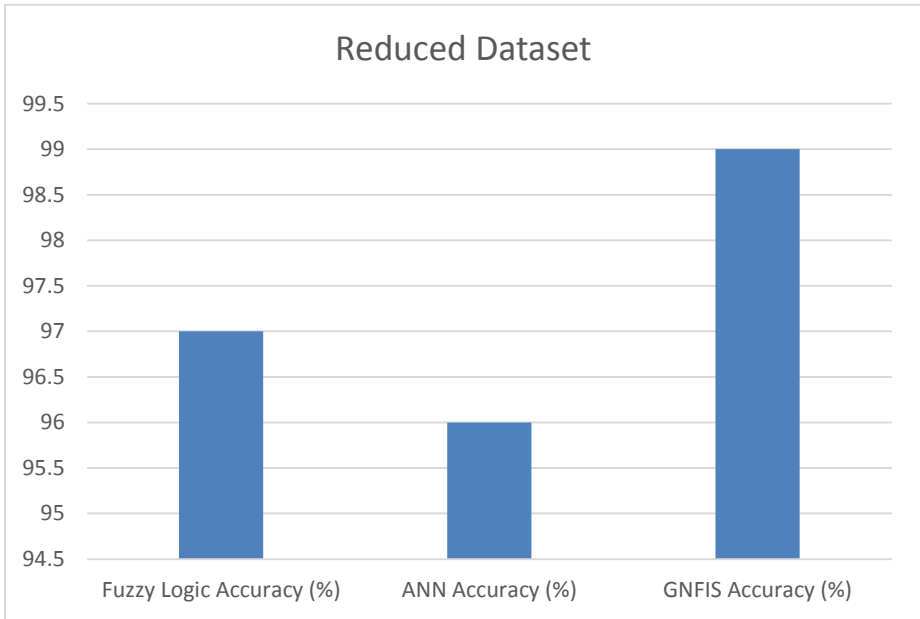
Fig. 3. The accuracy (%) for the three system for diabetes diagnosis

6   Conclusion and Recommendation

Test findings showed that the GNFIS works best, with 96% accuracy over the entire dataset being used. The Fuzzy logic model provided 94% accuracy. With 92% accuracy of the three models, the ANNs model registered the least accuracy. From the sensitivity study, as shown in Table 3, age, diabetes family history, BMI, and salty food preference played a significant role in the occurrence of the diabetes dataset, and the findings provide proof of diabetes prevention through community interventions. This research introduced Genetic Algorithms for dimensionality reduction, as well as Neural Network and Fuzzy Logic for diagnosing the data set for diabetes. The GNFIS analysis of the proposed system's accuracy is 2.08% higher than the neural network and the fuzzy logic. However, the accuracy of the system can be increased using other combinations of other machine learning algorithms. Besides, this application runs on a standalone system. In future work, the system can be applied on high-performance client-server and mobile applications, thus client-server application installed can request and receive information over the network which will be easier to access by all users.

References

1. Alade, O.M., Sowunmi, O.Y., Misra, S., Maskeliūnas, R., Damaševičius, R.: A neural network based expert system for the diagnosis of diabetes mellitus. In: Antipova, T., Rocha, A. (eds.) MOSITS 2017. AISC, vol. 724, pp. 14–22. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-74980-8_2

2. International Diabetes Federation. IDF Member Association Consultation on Diabetes Priorities for the UN Summit on NCDs. Brussels (2010)

3. Jimoh, R.G., Afolayan, A.A., Awotunde, J.B., Matiluko, O.E.: Fuzzy logic based expert system in the diagnosis of ebola virus. Ilorin J. Comput. Sci. Inf. Technol. **2**(1), 73–94 (2017)

4. Ameen, A.O., Olagunju, M., Awotunde, J.B., Adebakin, T.O., Alabi, I.O.: Performance evaluation of breast cancer diagnosis using radial basis function, C4. 5 and adaboost. Univ. Pitesti Sci. Bull. Ser. Electron. Comput. Sci. **17**(2), 1–12 (2017)

5. Iheme, P., Omoregbe, N., Misra, S., Ayeni, F., Adeloye, D.: A decision support system for pediatric diagnosis. In: M. F. Kebe, C., Gueye, A., Ndiaye, A. (eds.) InterSol/CNRIA -2017. LNICST, vol. 204, pp. 177–185. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-72965-7_17

6. Nonso, N., Farath, A., David, E., Jiten, V., James, N.: Model for type 2 diabetes management: a tool for regimen alterations. J. Comput. Sci. Appl. **3**(3), 40–45 (2015)

7. Lindner, L.M.E., Rathmann, W., Rosenbauer, J.: Inequalities in glycaemic control, hypoglycemia, and diabetic ketoacidosis according to socio-economic status and area-level deprivation in type 1 diabetes mellitus: a systematic review. Diab. Med. **35**(1), 12–32 (2018)

8. Abdulrahman, M., Husain, Z.S., Abdouli, K.A., Kazim, M.N., Ahmad, F.S.M., Carrick, F.R.: Association between knowledge, awareness, and practice of patients with type 2 diabetes with socio-economic status, adherence to medication, and disease complications. Diab. Res. Clin. Pract. **163**, 108124 (2020)

9. Oladipo, I.D., Babatunde, A.O.: Framework for genetic-neuro-fuzzy inferential system for diagnosis of diabetes mellitus. Ann. Comput. Sci. Ser. **16**(1) (2018)

10. Oladipo, I.D., Babatunde, A.O., Aro, T.O., Awotunde, J.B.: Enhanced neuro-fuzzy inferential system for diagnosis of diabetes mellitus (DM). Int. J. Inf. Process. Commun. (IJIPC) **8**(1), 17–25 (2020)

11. Persson, M., et al.: The better diabetes diagnosis (BDD) study – a review of a nationwide prospective cohort study in Sweden. Diab. Res. Clin. Pract. **140**, 236–244 (2018). https://doi.org/10.1016/j.diabres.2018.03.057

12. Kaur, C., Omisakin, O.M.: Data mining methods to improve clinical trials in diabetic patients. Ann. Clin. Lab. Res. **06**(04), 1–9 (2018). https://doi.org/10.21767/2386-5180.100266

13. Rinsho, N., Sugihara, S.: Diagnosis and treatment of type 1 diabetes mellitus in children. Jpn. J. Clin. Med. 74, 501–505 (2016)

14. Pandey, S., Tripathi, M.M.: Diagnosis of diabetes using artificial intelligence techniques by using biomedical signal data. Int. J. Res. Dev. Appl. Sci. Eng. **13**(2), 1–6 (2017)

15. Ayo, F.E., Awotunde, J.B., Ogundokun, R.O., Folorunso, S.O., Adekunle, A.O.: A decision support system for multi-target disease diagnosis: a bioinformatics approach. Heliyon **6**(3), e03657 (2020)

16. Thirugnanam, M., Kumar, P., Vignesh, S., Nerlesh, C.R.: Improving, the prediction rate of diabetes diagnosis using fuzzy, neural network, case-based (FNC) approach. Proc. Eng. **38**, 1709–1718 (2012). https://doi.org/10.1016/j.proeng.2012.06.208

17. Awotunde, J.B., Matiluko, O.E., Fatai, O.W.: Medical diagnosis system using fuzzy logic. Afr. J. Comput. ICT **7**(2), 99–106 (2014)

18. Azeez, N.A., et al.: A Fuzzy expert system for diagnosing and analyzing human diseases. In: Abraham, A., Gandhi, N., Pant, M. (eds.) IBICA 2018. AISC, vol. 939, pp. 474–484. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-16681-6_47

19. Durairaj, M., Kalaiselvi, G.: Prediction of diabetes using the backpropagation algorithm. International Journal of Emerging Technology and Innovative Eng. **1**(8), 21–25 (2015)

20. Abdullah, A.A., Fadil, N.S., Khairunizam, W.: Development of a fuzzy expert system for the diagnosis of diabetes. In: 2018 International Conference on Computational Approach in Smart Systems Design and Applications (ICASSDA), pp. 1–8. IEEE August 2018

21. Nilashi, M., Ibrahim, O., Dalvi, M., Ahmadi, H., Shahmoradi, L.: Accuracy improvement for diabetes disease classification: a case on a public medical dataset. Fuzzy Inf. Eng. **9**(3), 345–357 (2017). https://doi.org/10.1016/j.fiae.2017.09.006
22. Qureshi, I., Ma, J., Abbas, Q.: A recent development in detection methods for the diagnosis of diabetic retinopathy. Symmetry **11**(6), 1–34 (2019). https://doi.org/10.3390/sym11060749
23. Thompson, T., Sowunmi, O., Misra, S., Fernandez-Sanz, L., Crawford, B., Soto, R.: An expert system for the diagnosis of sexually transmitted diseases–ESSTD. J. Intell. Fuzzy Syst. **33**(4), 2007–2017 (2017)
24. Omisore, M.O., Samuel, O.W., Atajeromavwo, E.J.: A genetic-neuro-fuzzy inferential model for diagnosis of tuberculosis. Saudi Comput. Soc. King Saud Univ. Appl. Comput. Inform. **13**, 27–37 (2017)
25. Uğuz, H.: A biomedical system based on artificial neural network and principal component analysis for diagnosis of the heart valve diseases. J. Med. Syst. **36**(1), 61–72 (2012)
26. Tejashri, N.G., Satish, R.T.: Prognosis of Diabetes using Neural Network, Fuzzy Logic, Gaussian Kernel Method. Int. J. Comput. Appl. 0975–8887, **124**(10), 21–34 (2015)
27. Iheme, P., Omoregbe, N.A., Misra, S., Adeloye, D., Adewumi, A.: Mobile-Bayesian diagnostic system for childhood infectious diseases. In: ICADIWT, pp. 109–118 July 2017