Diagnostic and Therapeutic Model for Real Time Management of Diabetes

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ABSTRACT

Diabetes is a major health problem inherent to people at all age groups in developing countries. Conventionally, diagnosis of this condition was based on blood sugar level however, its effect can be traced from other symptoms such as Body Mass Index, and Blood Pressure. This paper presents a decision support model that can be used by diabetic patients and medical practitioners for diagnosis and therapy of diabetes. Fuzzy Logic was adopted for diagnosing pre-diabetic and diabetic patients' data from Obafemi Awolowo University Teaching Hospital Complex, Ile-Ife, Osun-State, Nigeria. Therapy is provided as personalized diet recommendation using person correlation coefficient and users' preferences. System evaluation shows adorable performance on both operations.

CCS Concepts

• Information systems →Information retrieval →Retrieval tasks and goals → Recommender systems

Keywords

component; Diabetes Mellitus; Medical Diagnosis; Recommender System; Fuzzy Logic; Diet Personalization

1. INTRODUCTION

As mechanization, urbanization, globalization, financial and social developments led to richer and better life in human daily affairs, modifications and alterations in diets have brought about greater chances of developing certain diseases (FAO, 2013). Food choice selection has immense effect on health as hale diets help sustain balanced body weight, enhanced growth, and boost immune system thereby promoting good mental function for daily activities. Medical research has shown that healthy foods strengthens the immune system thereby presenting people a greater chance of countering free radicals and warding off diseases[1]. Simply, healthy diets are dietary taken to develop and repair body cells and tissues for body effective function. Contrarily, poor dietary lifestyle is a key contributor to development of chronic diseases such as obesity, diabetes, and cardiovascular diseases [2].

In the world today, millions of people suffer from poor health conditions as a result of inappropriate diets [3]. For instance obesity, which has potentials of causing more severe problems, has being a popular health condition around the world. In a finding by Sharma & Majumdar, 68% of women between 21 and 52 years live with obesity [4]. Obesity occurs when excess fat accumulates in body thus reduces life expectancy. In conventional medicine, obesity is not regarded as chronic disease but it leads to serious health conditions like diabetes mellitus, cardiovascular diseases (CVD), which have high mortality rates [5].

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The adoption of Information Technology in modern societies has experienced a shift of paradigm in health condition management. Most people consume foods without considering their health state either because they were not properly guided or due to unavailability of medical experts. Medical procedures have been supported by technology advancement to minimize the rapid growth of chronic diseases like diabetes [6]. Moreover, recommender system (RS) assumes information from beneficiary or his closer neighborhood to give suggestions for making optimal decision while faced with different choices [7].

Recent developments in different fields such as Health and Commerce RS have adopted the development of expert systems to support their business logics [8]. Such advancement could play a major role in disease control by providing accurate and reliable diagnosis results, acknowledgement of risk status. The central problems aim is building artificial life, reasoning and programming, knowledge representation, and understanding cognitives of natural language with adoption of Artificial Intelligence (AI) in machines. For instance, Ali & Mehdi [9] applied fuzzy concept to reduce risks associated with conventional practices in health diagnosis. AI techniques were mostly applied in diagnosis of cardiovascular, parasitic, and viral related diseases [10] however, obesity and diabetics has recently received some recognition [6][11][12]. In Babalola et.al. [6], real time diagnosis system was proposed to detect severity of diabetes in patients.

In e-Health, RSs can be utilized for therapy by predicting or recommending types of food people can take to preclude them from certain ailments. As a result, an intelligent meal planning system was proposed in [13] and similarly, Napat et al. [14] presented a knowledge-based approach for personalized food recommender. Furthermore, clustering analysis is adopted in Phanich et. al [15] to recommend food items for diabetic patients. Hsu et al. [16] also developed an online system that searches food composition databases, calculates dietary intake, and provides the guidance for decision making in nutrition counseling.

Despite the adoption of RS for diet related diagnosis and preventive-therapy, suitable food selection are still difficult for some people especially in the presence of many factors. Hence this work extends the model in [6] with recommender component that predicts type and quantity of foods that can be taken for effective management of diabetes. The remaining parts of this paper is organized that Section 2 presents review of related works; Section 3 presents the diagnostic RS for managing pre-diabetic and diabetic patients. Experimentation, Results and evaluation of experiments carried out are presented in Section 4. Lastly, conclusion and futures works are presented in Section 5.

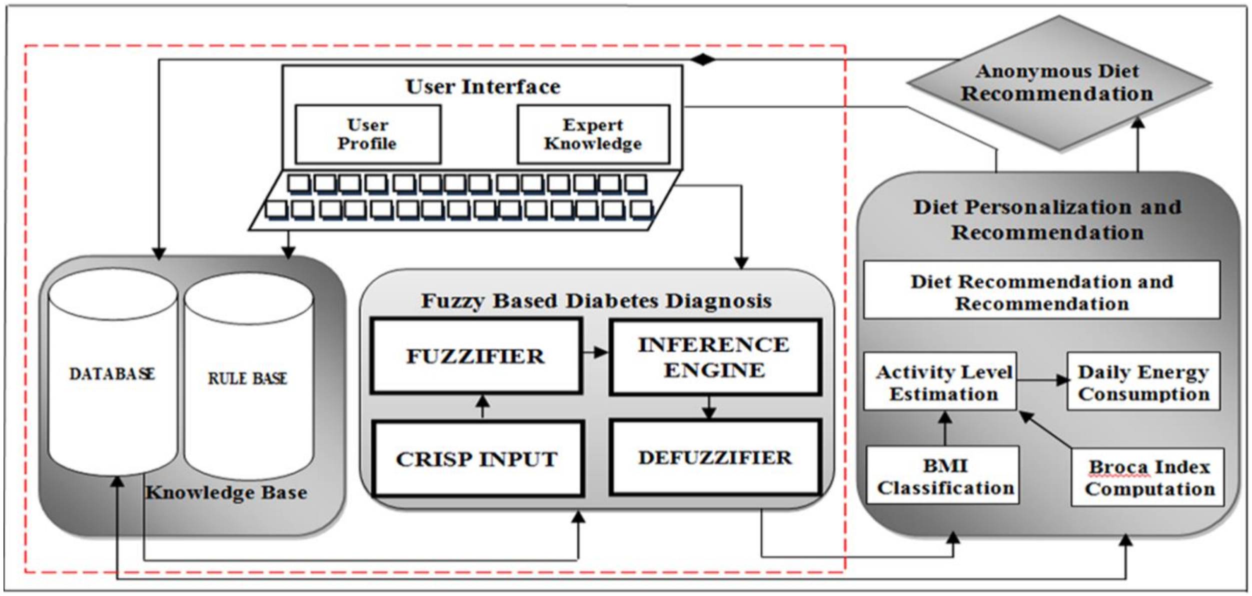


Figure 1. Architecture of a Fuzzy Based Diet Recommender System

2. SYSTEM DESIGN AND ANALYSIS

Architecture of the model for real time management of diabetes is presented in Fig. 1. The baseline model was described in [6] though without enhancement for recommendation thus, this model shows capability of diagnosis of diabetes and food recommendation base on patient health data.

2.1 Fuzzy-Based Diagnosis

The system architecture has four major components working inter-connectedly to perform diagnosis of pre-diabetic and diabetic patients and recommendation of food items base on patient diabetic or obesity level. The diagnostic part combines efforts from Graphical User Interface, Knowledge base, and Fuzzy Logic components to determine patients' health status. Recommender component has roles to play when a user demands recommendation anonymously or as a basis for food therapy. A detailed functions of the first three components that is: User Interface, Knowledge Base and Fuzzy Logic; were detailed in [6]. In a nutshell, the functions are:

a. Patients' data were collected and stored for processing through graphical user interface in an efficient manner;
b. Raw and processed data are stored in the database component of knowledge base together with if-then rules upon which fuzzy logic component operates; and
c. Fuzzy inference component operates on user's data for purpose of diabetic diagnosis. Fuzzification and defuzzification were applied to handle imprecise and uncertain information innate in patients' data.

The defuzzification process translates output from fuzzy inference engine to crisp values through computationally simple and accurate technique: Centroid of Gravity (CoG). Given as an aggregated membership function with x_i as center of the membership function, the output value is determined as with Eq1.

$$\mathrm{CoG}(Y') = \frac{\sum_{i=1}^{n} \mu_Y(x_i)x_i}{\sum_{i=1}^{n} \mu_Y(x_i)} \quad . \quad . \quad . \quad Eq.(1)$$

2.2 Food Recommendation

All patients whose data are passed for diagnosis are lamed pre-diabetic. However, diagnostic component of the model is used determine the true health status of patients. People could be lamed diabetic if their body weight signifies being overweighed or obese. To determine if a patient is obese, the Body Mass Index value is obtained using Eq 2.

$$\mathrm{BMI} = \frac{w(kg)}{h^2(cm^2)} \quad . \quad . \quad . \quad .(2)$$

where w(kg) is the patient's weight in kilogram, and $h^2(cm^2)$ is height in centimeter.

Then patient is classified as being underweight, normal, overweight, or obese base on categorization in Eq 3.

$$\mathrm{Cat} = \begin{cases} \mathrm{BMI} < 18.5 & \rightarrow \quad \mathrm{Underweight} \\ 18.5 \leq \mathrm{BMI} \leq 24.9 & \rightarrow \quad \mathrm{Normal} \\ 25.0 \leq \mathrm{BMI} \leq 29.9 & \rightarrow \quad \mathrm{Overweight} \\ \mathrm{BMI} \geq 30.0 & \rightarrow \quad \mathrm{Obese} \end{cases} \quad .(3)$$

Therapeutic action is triggered if a person classified obese is also confirmed diabetic by the diagnostic processes, or request is voluntarily made for food recommendation.

1) Recommendation for Diabetic Personality

In cases where lamed patients are diagnosed diabetic, the recommendation component uses Broca Index to compute ideal body weight (bw) of the patient. Broca Index is an ideal body mass measurement developed for standard weight computation [17]. The index value is obtained as in Eq 4.

$$\text{Ideal body weight} = \text{ body height(in cm)} - 100 \quad ...(4)$$

Broca Index value is used to determine the activity level (AL) of a patient. Activity level of a patient has intrinsic characteristic with total calorie of energy such patient requires daily, and it is determined by combining BMI value of patient with his/her work category. Classification of works done by people based on expected energy to achieve optimal result is reported in [18]. This research combines classification advice by authors with BMI values in categorizing patients to AL groups, as presented in Table 1.

Table 1. Activity level (AL) categorization.

BMI	Sedentary	Active	Very active
Obese	30	35	40
Overweight	25	30	35
Normal	20	25	30
Underweight	15	20	25

Therefore, a preferred three-square meal ration is applied base on case study disease. In the case of diabetes, 3:4:3 ration is applied for Breakfast, Lunch, and Dinner respectively. The basic goal is to eat healthy foods in reasonable proportions alongside time of the day since diabetic patients are keenly monitored to avoid blood sugar spikes. Since more energy is required in afternoon period, it is important such patients consume more calories in the afternoon rather than morning or night. Summarily, rations needed for consumption by diabetic patients is given as Eq. 5

$$\mathrm{kcal}(P_i) = r_i(bw * AL) \quad . \quad . \quad . \quad . (5)$$

where kcal is the kilocalorie for Period of a day, is ration for , and AL is activity level category of patient.

The periodic kilocalorie intake is further shared to three macro food nutrients: carbohydrate, protein and fat. Sharing percentages of macro food nutrients strongly depend on diabetic level of patient. According to American Diabetes Association [19], low carbohydrate meals are good to keep blood glucose levels in diabetic patients within normal range, and offer tasty meals that satisfy hunger. Such lowness inversely depends on diabetes level of the patient. Relationships between diabetes level and percentages of macronutrients in diabetic meals are given in Table 2. Percentage ratios were computed and displayed as users' guide. The output is a seven-day food plan recommendation based on food roster pre-stored in the database. Dynamism in recommendation depends on history, allergic foods, favorite foods, and diabetic health status of patients.

Table 2. Diabetic Levels and Macro Food Nutrient Percentage.

Diet	Carbohydrate	Protein	Fat
Normal	60%	20%	20%
Mild Diabetic	56%	23%	21%
Severe Diabetic	50%	26%	24%
Very Severe Diabetic	45%	30%	25%

The model present patients with substitutes for allergic foods using correlation measure, this is detailed in voluntarily request recommendation. Finally, for conveniences, food items are converted into grams on display to enable patients prepare their meals correctly and independent of nutritionists. Conversions of the macro nutrients adopted from [6] is presented in Eq 6.

$$\begin{aligned} 1\text{g of carbohydrate} &= 4\text{kcal of carbohydrate} \\ 1\text{g of protein} &= 4\text{kcal of protein} \qquad . \quad . (6) \\ 1\text{g of fat} &= 9\text{kcal of fat} \end{aligned}$$

Aside these macro nutrients, traces from other food nutrients such as vitamins, water are also considered for personalization.

2) Recommendation on Voluntarily Request.

In first part of the recommendation module, the model exhibits a curative mechanism for pre-diabetic patients who were registered with the system and diagnosed. On another side, the model has a preventive component that predicts food items for users who were never lamed pre-diabetic nor diagnosed by the system. This recommendation actuates on voluntary request by anonymous user using Pearson Correlation Coefficient for similarities measures.

Pearson Correlation Coefficient (PCC) measures distance between items that are linearly related. Unlike Euclidean distance measure, PCC observes correlations of variables in range of -1 to +1, hence accuracy of score is maintained when data is not normalized. In any voluntary recommendation request, users are obliged to specify a set of food items preferable to them as a meal. PCC is employed to retrieve groups of food-item combination(s) that are found closest to user's specification. For instance if a user specifies an item-set $S = \{X, Y, \ldots, Z\}$ and $X = \{x_1, x_2, \ldots, x_n\}$ where X,Y or Z are food items in a user's choice, and x_i is a major nutrient in food-item X, then groups of food items are recommended from the database following correlation procedures in Eq. 7.

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \ldots\ldots\ldots\ldots (7)$$

where $\bar{x}$ and $\bar{y}$ are mean values of nutrients x_i and y_i with confidence value such that $0.5 \leq r \leq 0.95$. Two set of food are correlated if they have a high confidence value.

3. EXPERIMENTS AND RESULTS

This section reports details of experiment carried out to validate the proposed model. Details of the dataset used and results are detailed in this part. Results from some related works were taken as basis for performance measure.

3.1 Dataset

The dataset used were sourced from multiple agents including nutritionists, diet related publications and websites. Since diabetic patients can only feed on certain foods, we design a template made from foods mostly consumed by diabetic people only. The template is a flexible seven-day calendric roster shaped with the help of nutritionists.

Guided by nutritionists, we established some relationships between diabetes level and amount of kilocalories patients can consume from macro nutrients in foods to provide diet personalization for diabetic patients. Finally, a list of 70 food items consumable by diabetic patients were crawled from diet related websites, and analyzed. The macro- and micro- features were elicited and stored in the database schematically as shown in Table 3.

These features offer cognitive help in personalized and anonymized food items recommendation. Food combination strictly follows a model base on nature combination where nature of food items is assumedly derived from their appearance. Nature can be any of the options in Table 4.

3.2 Experimental Result

Data of thirty pre-diabetic patients from Obafemi Awolowo University Teaching Hospitals (OAUTHC), Ile-Ife, Osun State, Nigeria was fed into the system for purpose of diagnosis and food therapy.

Table 3. Classification of Food Items for Possible Combination

Id	Nature	Example	Id	Nature	Example
1	Solid (Grain)	Rice	8	Soup Add-it	Locust beans
2	Flour Food	Bread	9	Moisty	Beans pottage
3	Liquid	Pap	10	Fruit	Apple
4	Beverage	Milk	11	Solid Grain Support	Fish Stew
5	Diary	Egg	12	Liquid Support	Akara
6	Tuber	Boiled cocoyam	13	Flour Food Support	Mayonnaise
7	Soup	Ugwu with Melon	14	Tuber Support	Groundnut oil

Table 4. Feature Set of Foods for Personalized Recommendation

Description	Macro Nutrient In Food			Multi Vitamins						Others			
	Carbohydrates	Protein	Fats	A	C	E	B6	B12	D	Salt	Fibre	Gram/Serving	Nature

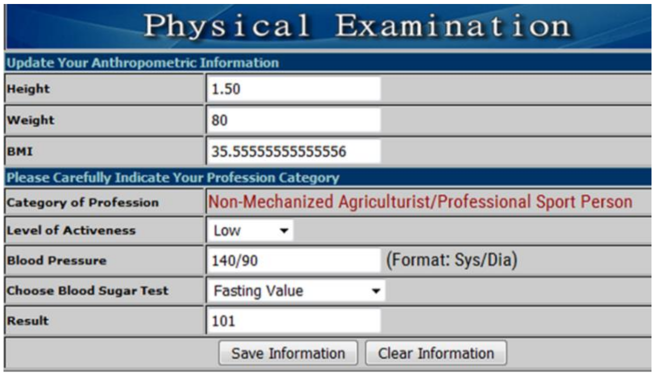


Figure 2. Patients' Information Form (Case Study of Patient 013)

This is to validate preciseness of personalization in recommendation made by the proposed system. All program codes are implemented with HTML, PHP, JavaScript and SQL. The HTML tags and Java scripts are employed to structure the outlook and behavior of the web pages respectively. At each session, anthropometric data and vitals of patients are captured with web interface displayed as Fig. 2. Following the diagnosis processes evaluated by the Fuzzy-Based component, users' Diet Personalization and Recommendation is operated on at actual modules.

Upon successful fuzzification process, the diagnosis result for each patient is displayed as in Fig. 3. The interface has two parts: the first shows result of fuzzy operation on left side, and a summary panel on the right side. The later displays diagnosis status and level of severity of diabetes in patients. Also on the later side are controls for personalizing foods to be recommended for patients, alongside with patient diet history. Data of the 30 subjects and respective diagnosis are given in Table 5. Diagnosis by fuzzy component shows Patient 013 is severely diabetic, hence appropriate eating formula to be selected is 3:4:3.

To recommend personalized food items, "Continue to Prediction" button in Fig. 3 is clicked. Once the procedure is triggered, the recommender acquires diagnosis result and selected eating formula as essential information needed to fine-tune the pre-designed seven days template for food personalization and recommendation.

Table 5. DiAgnosis Result of 30 Pre-Diabetic Patients

Id	Crisp Val	Status		Id	Crisp Val	Status		Id	Crisp Val	Status
01	11.77%	Normal		11	30.26%	Mild		21	44.20%	Mild
02	24.28%	Normal		12	18.08%	Normal		22	45.64%	Mild
03	24.28%	Normal		13	77.69%	V. Severe		23	81.35%	V. Severe
04	30.26%	Mild		14	23.23%	Normal		24	95.47%	V. Severe
05	43.06%	Mild		15	99.77%	V. Severe		25	42.23%	Mild
06	71.89%	Severe		16	92.55%	V. Severe		26	56.78%	Severe
07	54.28%	Mild		17	88.49%	V. Severe		27	83.31%	V. Severe
08	56.85%	Severe		18	23.08%	Normal		28	11.17%	Normal
09	84.14%	V. Severe		19	61.01%	Severe		29	46.05%	Mild
10	14.17%	Normal		20	66.12%	Severe		30	24.39%	Normal

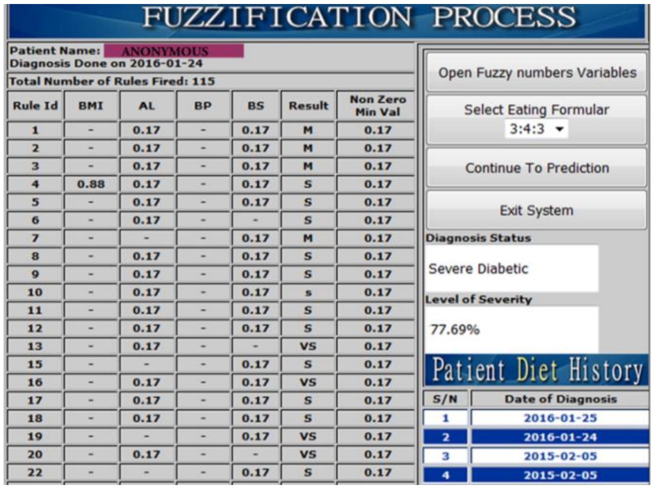


Figure 3. Result of Fuzzy-Based Diagnosis (Case Study of Patient 013)

3.3 Diet Personalization and Recommendation

In this phase two procedures carried out seamlessly are personalization and recommendation of food items for users. During personalization, ideal body weight of a patient is used to determine the total Energy Required Daily (ERD) in kilocalories. This includes certain Proportion of Breakfast, Lunch and Dinner (PoB, PoL, PoD) of food items with proportions depending on selected eating formula, and pre-configured percentage of macro food nutrients for different levels of diabetes as explained in Table 2 of Section 3.To compute ideal body weight of a patient, Broca Index estimated from patient's height is utilized. Then, the total amount of food to be consumed per day is computed following procedures in Section 3.

Patient 013, in his session with the system, supplied values in Fig. 2 and has severe diabetic as diagnosis result. The patient claims a height value of 1.50 hence a Broca Index of 50 was computed and thereby, a total of 1750 kcal is to be consumed daily. Still on personalization, selected eating formula was applied to determine portions for breakfast, lunch and dinner as given in Table 6.

Table 6. Breakfast, Lunch and Dinner Food Proportion.

Breakfast Portion	Lunch Portion	Dinner Portion
PfB = $^{3}/_{10}$ * kCal => **525**	PfL = $^{4}/_{10}$ * 1750 => **700**	PfD = $^{3}/_{10}$ * 1750 => **525**

Furthermore, the three-square meals were subdivided by major food nutrients: carbohydrate, protein, and fat; hence we applied daily proportion for each of breakfast, lunch, and dinner to a suitable diet configuration base on patient's diabetic severity to compute appropriate proportion of macro food nutrient as in Table 7.

Finally, gram equivalents of items in food template were determined as personalized diet recommendation. Diets recommended by the model are presented to users in a single interface with ranking done based on users' favorites. This results in having foods that a user likes at top of the list while allergic ones come last in the auto-adjusted 7-day plan.

Pearson correlation explained in Section 3 was used to pair food items for meals recommended in any seven-day plan. The main role of Pearson coefficient is to generate balanced diet meal by observing correlation among food items in the database. In combination like ***Amala*** + ***Okra*** + ***Mackerel Fish*** + **Orange**, each food item are connected with

Table 7. Proportion of macro food nutrient (KCAL) for user "013"

	Carbohydrate	Protein	Fat
Breakfast	**CPFB** $= \frac{50}{100} * 525 = 262.5$	**PPFB** $= \frac{25}{100} * 525 = 131.25$	**FPFB** $= \frac{25}{100} * 525 = 131.25$
Lunch	**CPFL** $= \frac{50}{100} * 700 = 350$	**PPFL** $= \frac{25}{100} * 700 = 175$	**FPFL** $= \frac{25}{100} * 700 = 175$
Dinner	**CPFD** $= \frac{50}{100} * 525 = 262.5$	**PPFD** $= \frac{25}{100} * 525 = 131.25$	**FPFD** $= \frac{25}{100} * 525 = 131.25$

specific alternatives across different food items of the same ***Nature*** **(**See Table 4), and compute correlation score for each combination. For instance, coefficient algorithm combines each of **Amala**, **Eba**, **Fufu**, **Pounded Yam**, **Wheat**, and **Semolina**; with alternative items in other food natures to check correlation.

As a result fixed content of food roster template are updated with meal combinations that has best correlation. This is a direct function of Confidence Value (CV) varying between 0-1. However, only combinations with $CV \geq 0.5$ were considered for recommendation as in Table 8.

Another important part is personalization of food items which are recommended by filtering patient's allergen. Actually, recommendation interface has information displayed in two parts. The left side contains basic data of patient together with information on quantification of food-per-day (FPD), diet configurations with gram equivalent of foods, and patient's allergic foods, while the right side is actual recommendation made for patient. For each item in recommended plan, the diet system sorts out available substitutes for allergies using Euclidean distance given as

Table 8. Pearson Coefficient Correlation of Food Items

S/N	Food Item Combination	CHO	Protein	Fat	Salt	Fibre	A	C	E	B6	B12	D	CV
1	**Amala**	20	3	0	0	2.1	57	51	73	55	724	0.5	0.885
	Carrot	5.61	1	0.3	0	3.1	120	7000	206	220	0	0	
	Mackerel Fish	5.9	21.1	2.8	5.9	0	0	0	0	0	0	0	
	Ewedu	0.3	1.8	1.4	0.5	0	37	0	115	129	883	0.5	
2	**Boiled Pumpkin Vegetable**	1.4	0.2	0	0	0.3	1398	1300	200	0	0		0.883
	Pounded Yam	20	3	0	0	0.8	73	13	196	13	837	0.3	
	Beef Meat	0	7	3	1.7	0	14	35	191	21	402	0.6	
	Carrot	5.61	1	0.3	0	3.1	120	7000	206	220	0	0	
3	**Eba**	20	3	0	0.3	0.2	82	61	76	0	1286	0.4	0.881
	Beef Meat	0	7	3	1.7	0	14	35	191	21	402	0.6	
	Carrot	5.61	1	0.3	0	3.1	120	7000	206	220	0	0	
	Boiled Pumpkin Vegetable	1.4	0.2	0	0.3	0.3	1398	1300	200	0	0	0	
4	**Eba**	20	3	0	0.3	0.2	82	61	76	0	1286	0.4	0.876
	Carrot	5.61	1	0.3	0	3.1	120	7000	206	220	0	0	
	Mackerel Fish	5.9	21.1	2.8	5.9	0	0	0	0	0	0	0	
	Boiled Pumpkin Vegetable	1.4	0.2	0	0.4	0.3	1398	1300	200	0	0	0	
5	**Pounded Yam**	20	3	0	0	0.8	73	13	196	13	837	0.3	0.854
	Carrot	5.61	1	0.5	0	3.1	120	7000	206	220	0	0	
	Duck	0.9	19	28	0.2	0	210	0	700	180	3	0	
	Boiled Pumpkin Vegetable	1.4	0.2	0	0.4	0.3	1398	1300	200	0	0	0	

:

$$N_E(\hat{q}_A, \hat{q}_B) = \frac{1}{\sqrt{N}} \left(\sqrt{\sum_{j=1}^{N} |q_A^j - q_B^j|^2} \right). \quad . \quad . \quad (8)$$

where $\hat{q}_A$ and $\hat{q}_B$ are alternative food items q_A^j and q_B^j are j^{th} respective values of their nutrients.

In Fig. 4, Patient 013 indicates allergy to Pap, amongst other recommended food items, a sample of food items filtered out as substitute with the same nature is shown in Table 9. Substitutes are arranged in ascending order of their distance measure to Pap as Agidi, Quaker Oats, and Corn Flakes.

Table 9. List of Food Substitute(Pap)

Item	CHO	Protein	Fat	Vit A	Vit B	Vit C	Vit B_6	Vit B_{12}	Vit D	
Pap	15	3	0	5	8.6	0.78	5.1	5.99	0.8	E_d(pap, x)
Agidi	20	3	0	6.8	9.9	0.48	2.3	5.36	0.1	3.383859
Quaker Oats	15	5	0	9.6	6.4	1.53	9.7	7.5	0.3	3.785648
Corn Flakes	15	5	0.9	6	9.7	3.65	16.2	10.77	0	5.452991

Finally, the recommendation on voluntarily request only requires the Pearson correlation between the food items to locate a set of foods that are similar to user' selection. Previous works emphasized this in different RS [26][27].

3.4 System Evaluation

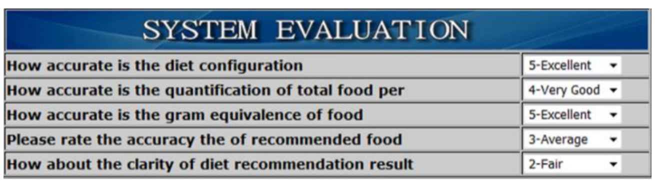
Evaluation is necessary for validation of application systems in general, but effectiveness is a measure of focus in personalizing diet recommendation systems. Since the system handles two important aspects of life, evaluation is separated as diagnosis error and user's preference on recommendation features. For diagnosis, we checked the sensitivity of underlying mathematical models to observe how it responds to inputs. This was done by comparing automated diagnosis results with conventional human approach, hence utilized Eq. (9) to compute the ratio of properly diagnosed patients (True Positive value) to total number of patients diagnosed with the system.

$$Sensitivity = \frac{True\ Positive}{Total\ Patients} * 100 \qquad Eq. (9)$$

Table 10. Diagnosis Results by Proposed System and Expert

Id	Proposed System	Medical Expert	Id	Proposed System	Medical Expert	Id	Proposed System	Medical Expert
01	Normal	Normal	11	Mild	Normal	21	Mild	Mild
02	Normal	Mild	12	Normal	Normal	22	Mild	Mild
03	Normal	Normal	13	V.Severe	V.Severe	23	V.Severe	Severe
04	Mild	Mild	14	Normal	Normal	24	V.Severe	V.Severe
05	Mild	Mild	15	V.Severe	Severe	25	Mild	Severe
06	Severe	Mild	16	V.Severe	V.Severe	26	Severe	Severe
07	Mild	Mild	17	V.Severe	V.Severe	27	V.Severe	V.Severe
08	Severe	V.Severe	18	Normal	Normal	28	Normal	Normal
09	Severe	Severe	19	Severe	Severe	29	Mild	Mild
10	Normal	Normal	20	Severe	Normal	30	Normal	Normal

Therefore, results obtained from manual approach were compared with observations by the proposed system as presented in Table 10. On comparing the diagnostic potential of the two approaches, the proposed system demonstrates a sensitivity value of 73.3%, hence the model's response to changes in input values is similar to human experts. We also evaluated effects of personalization in recommended diets. A routine call was included for dieticians to communicate their feedback about performance of the proposed system with regards to quality of recommended diets and patient personalization levels. This is to ensure reliability of parameters used in personalization and recommendation of food items. As shown in Fig. 4, five factors were used to observe users' preference, each could attain one of five Likert-scale values: 5-Excellent, 4-Very Good, 3-Average, 2-Fair, and 1-Poor.


SYSTEM EVALUATION

How accurate is the diet configuration	5-Excellent
How accurate is the quantification of total food per	4-Very Good
How accurate is the gram equivalence of food	5-Excellent
Please rate the accuracy the of recommended food	3-Average
How about the clarity of diet recommendation result	2-Fair

Figure 4. Evaluation Form for Personalization in Diet Recommendation

This evaluation part was based on view and responses of 10 randomly selected experts on diagnosis and therapy of diabetes at Obafemi Awolowo University Teaching Hospitals (OAUTHC), Ile-Ife, Osun State, Nigeria. Assessments done by experts using data of thirty pre-diabetic patients is summarized in Table 11.

Table 11. Summary of Responses from Diabetes Experts.

Parameters	Excellent	Very Good	Good	Fair	Poor
Accuracy of diet configuration	-	7	3	-	-
Accuracy of total FPD(kcal) quantification	-	6	3	1	-
Accuracy of gram equivalence in food	1	5	2	2	-
Accuracy of food recommendation	2	6	1	1	-
Clarity of recommendation	2	7	1	-	-

Quantification of the summary is a better way to describe user's preference on recommendation features, hence we had to compute a central value for rating purpose. In this evaluation, we assumed the parameters have equal weights, however weights of Likert scale values differs as in Fig. 4. Therefore, the system has an average rating of 74.8%, that is, 187 points out of 250 maximum points.

4. CONCLUSION

Diabetes Mellitus is a serious health condition that causes mal-absorption of foods to be used as energy in human body. It is costly to manage and as a result, appears as a major factor for high mortality rates in developing countries. Importantly, preventive measures against primary cause, which sometimes is malnutrition or obesity, aid healthy diet lifestyle, improve blood pressure, control blood sugar level and decrease the risk of health complications. This paper presents a scalable computer aided model for management of diabetes. Fuzzy logic is proposed for diagnosing diabetic levels in patients, and a personalized recommendation approached towards maintaining balanced macronutrients needed by patients just after diagnosis.

Diagnosis stage of the proposed system is basically to determine if a lamed patient is diabetic, in other words to determine the level of diabetes. However, the major proposal in this study is personalization of recommended foods. Recommendation initially emulates a seven-day template which serves as a basic food roster, and subsequently modified to suit different patients. Modification is based on diagnosis results of patients hence reaching a goal of personalization. The work done is a typical personalization in which foods recommended varies directly with total ERD by patients. Hence, the recommended seven-day food plan for each patient is filtered based on the diet history and allergies of such patients. Different sets of food items are selected and passed for ranking at each session.

The system has promising diagnosis accuracy and reliable average point for recommendation. Broca index adopted in this research is more efficient at recommending ERD for users, however, might not be the best for very severe diabetic patients, because there is great need to reduce their carbohydrate intake. Basically, accuracy of the system could be better if calorie recommendation method is adopted. Hence, future work scan adopt switching to Harris Benedict method for recommending daily calorie intake. Furthermore, it is good to note that Harris Benedict method also has limitation of over estimating calorie intake hence, only suitable for patients with very severe diabetes.

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