An Automated Balanced Nutritional Guidance system Based on Rough Sets

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Abstract— **Expert systems are computer applications which embody some non-algorithmic expertise for solving certain types of problems. Many researches adopted developing expert systems in medicine. In the case of disease, the patient is not discussed in the amount and type of medicine but in the case of nutrition there is a need to cover the gap between the recommendations and the current nutritional style. Since one needs to adopt the recommendations for a long life, these recommendations should be reasonably near from his current style. The rough sets which provide efficient methods, algorithms and tools for finding hidden patterns in data will be utilized to develop such system. This work aims to develop an expert system that can cover the gap between personal nutritional style and experts recommendations. The methodology that will be used in the current work is a modified system of NGMS that implemented NRIM-REX. A set of attributes will be added to the system to represent the nutritional style of the case and for each pattern a set of alternative sets of recommendations will be presented and a ranking measure for these recommendations will be added based on the nutritional style.**

Keywords- Rough Sets, Expert Systems, Inference Engine, NGES, Nutrition diagnosis system, Rule-based.

I. INTRODUCTION

Expert systems are computer applications which embody some non-algorithmic expertise for solving certain types of problems. For example, expert systems are used in diagnostic applications servicing both people and machinery. They also play chess, make financial planning decisions, configure computers, monitor real time systems, underwrite insurance policies, and perform many other services which previously required human expertise [1]. There are many reasons for building an expert system to solve health related problems. Human experts may not always be available or may even be absent from a location. Also, by pooling knowledge of many experts, an expert system may be better than one human expert in its overall performance. An expert system does not get tired and are expected to be more consistent. It can also be used for training and passing on the knowledge derived from the human experts [2].

Searching the literatures guide one to classify the application of expert system in nutrition field to some classes. The first group developed applications to solve nutrition problems like meal planning, Meal Planning, Surya and Singh presented a paper to describe the development of an Expert System, the Nutrition Diet Programme (NDP) for therapeutic meal planning, [3] , Soon and Gon developed a web expert system for nutrition counseling and menu management. This program manipulates a food, dish and menu and search database that has been developed. [4], Pinter et. al., presented MenuGene nutrition counseling expert system and its main components, focusing on home health monitoring / dietary logging. Published solutions so far can satisfy nutrient constraints, but does not take harmony rules into account [5].

The second group tried to evaluate either the quality of the data [6] or to assess the effects of computerized clinical decision support systems [7] or to assess the efficacy of a Web-based tailored behavioral weight management program [8] or to determine the feasibility of a workplace nutrition Web program or to use menu modeling was to evaluate the effects of gradual dietary changes on diet quality [9] or to analyzed dietary patterns in relation to health outcomes or disease risk factors [10] or to evaluate recent research regarding the use of computer-based nutrition education interventions targeting adolescent overweight and obesity [11].

The other class developed adjusted expert systems. These works tried to develop a new rule and new methods to build the rule induction and inference engine. Some works based on fuzzy theory, Leung and Lam presented a study for expert-system building. This article presented a comprehensive expert-system building tool, called System Z-11, that can deal with exact, fuzzy (or inexact) [11], Heinonen et. al., presented a fuzzy expert system for a nutritional guidance application [12], Petri et., al. developed a fuzzy expert system for a nutritional guidance application [13] .

Rough Set Theory, proposed in 1982 by Zdzislaw Pawlak, is in a state of constant development. Its methodology is concerned with the classification and analysis of imprecise, uncertain or incomplete information and knowledge, and is considered one of the first non-statistical approaches in data analysis [14]. The fundamental concept behind Rough Set Theory is the approximation of lower and upper spaces of a set, the approximation of spaces being the formal classification of knowledge regarding the interest domain. The subset generated by lower approximations is characterized by objects that will definitely form part of an interest subset, whereas the upper approximation is characterized by objects that will possibly form part of an interest subset. Every subset defined through upper and lower approximation is known as Rough Set [4]

Based on this theory, a program is developed, called NRIM-REX (Nutritional Rule Induction Method based on Rough Sets and Resembling methods for Expert systems), which extracts rules for an expert system from databases, and applies re-sampling methods to the estimation certainty factors of derived rules. This system is evaluated on the datasets of RHI- NOS domain. The results show that the proposed method induces NGES (Nutritional Guidance Expert System) classification rules correctly from databases and that resembling methods can estimate the performance of these rules and certainty factors.

The last 20 years of research and development in the field of artificial intelligence in medicine (AIM) show a path from knowledge-intensive systems, which try to capture the essential knowledge of experts in knowledge-based system, to data-intensive systems available today. Nowadays enormous amounts of information are accessible electronically. Large datasets are collected continuously monitoring physiological parameters of patients. This work presents a system to not only classify the pattern of nutritional cases but also to give the corresponding guidance patterns. In this work, an expert system will be presented depending on rough system theory; the system will be developed through two phases. Training phase, the nutritional information about each case will be recorded and the recommended advice regarding meal planning of real expert will be recorded. The expert transforms the crisp information corresponding to each case into non-crisp information. In front of each case the expert add his recommendation in a set of columns. These columns are labeled as expert opinion. NGES system is developed depending on rough sets. The rules gained through NGES will be implemented in NRIM-REX. This work concentrates on the recommendation that our system presents to the user. In the case of disease, the patient is not discussed in the amount and type of medicine but in the case of nutrition there is a need to cover the gap between the recommendations and the current nutritional style of the case. After defining the case of a given person. The system shows him a group of alternatives in which all of them are suitable for his case with a ranking recommendation. Also the system enable one to change the amounts or types of his food and give him alarm if his suggested combination is not suitable.

II. NUTRITION CARE PROCESS.

A. Selecting a Template (Heading 2)

The Culture in the gulf area makes the self control is difficult for the majority of the people. Most of them need an advisor who guide, monitor and give them instruction for short times. This gives the dietitians a special importance and essential role. Also a non trivial percent of the people who need nutritional care cannot even read and write. Based on these facts the system is developed to reflect the fact that the one who will use the system are the dietitians to help them to manage and support the nutrition care process.

Since a medical diagnosis does not change as long as the disease condition stays and nutrition diagnosis would change when patient changes his response. The nutrition diagnosis process is different from a medical one. Medical diagnosis is defined as pathological disorder of a particular organ or disease. The correct nutrition diagnosis (es) can be achieved through nutritional assessment that presents dietitians with a method to set realistic and measurable goals. Based on analyzing the gathered data, choosing fitting interventions, and mentoring improvement in achieving those expected goals. The nutrition diagnosis consists of three major components.

a) Problem (diagnostic label)

b) Etiology (cause/contributing factors)

c) Signs/symptoms (defining characteristics).

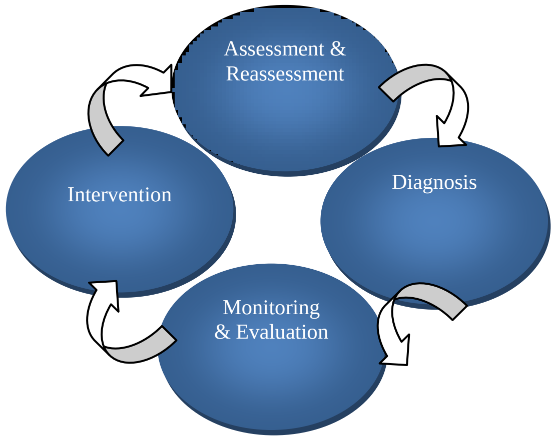

Figure 1. Nutrition Care Steps

Signs/symptoms data enable us to quantify the problem and allow us to evaluate and give a severity ranking. The patient expresses his status changes while the signs reflect the fluctuations in the patient's health status. The nutrition care process has basic steps. Any system, to be successful should document and update the documentation regularly for these steps as illustrated in Figure 1.

In the assessment and reassessment process: the system should enables the dietitians to obtain/collect appropriate data, analyze/ interrupt with evidence based standards and document.

In the diagnosis process: the system should help the dietitians to identify and label the problem, determine cause and contributing risk factors, cluster signs and symptoms characteristics and document.

In the intervention process the system should enable the dietitians to build, implement and document the action plan

1. Building an action plan of prioritize nutrition diagnosis depending on the status of thenutritional problem.Collecting evidence based practice guides.The Patient determinesthe expected outcome. The statements should beobvious, brief and expressed in a clear and measureableway. The patient evaluates the plan.

2. Implement nutritional intervention.During intervention process, dietitians try to effectively prsent the plan of care to the patient and convene him to execute the proposed actionplans. He/she should also regularly collect patient's data andmodifies the plan depending on the collected data as required.

In the monitoring and evaluation process: the system should help the dietitians to monitor the progress, measure outcome indicators, and evaluate the outcomes and document.

III. Architecture of the System

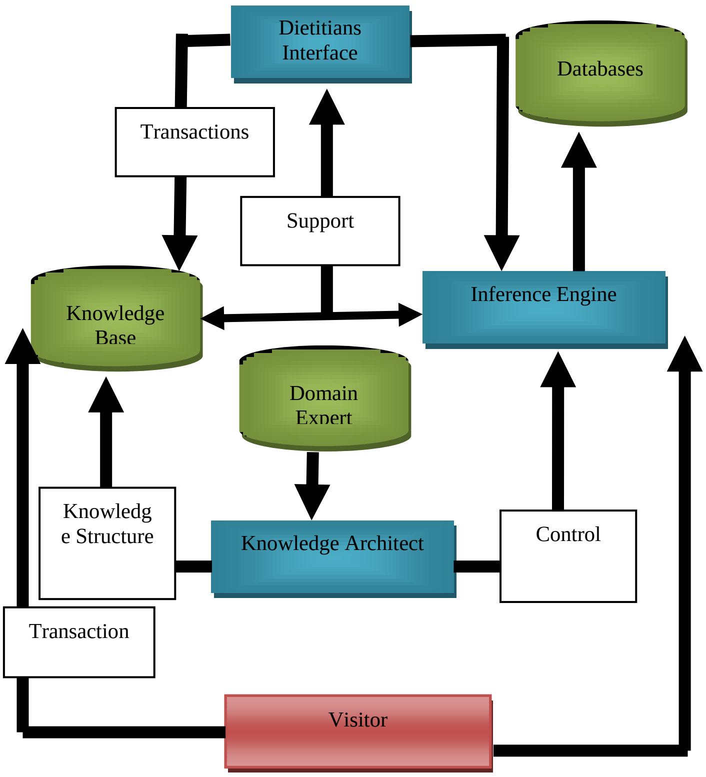

Figure 2. System Architecture

The main components of an expert system are 4 components [15].

1. **Working memory**: During program running, we need a working memory to store temporary the data and information.
2. **Inference Engine**: This core of any expert system. It is responsible to execute the rules that are stored in the rule base with forward or backward chaining.
3. **Knowledge base**: Traditionally a rule base with rules in the form: IF <conditions> THEN <action list> ELSE <action list> are used to represent the rules of inference. In this study a different approach will be adopted in building and inferring the rule base. This approach depends on rough sets which will be explained in the next section.
4. **Dietitians Interface**: We mean by a user interface the collection of screens that will appear to the dietitians and enable him to interact effectively with the system.

Usually the expert system has an Explanation Facility to explain the transition process among the rules to reach a conclusion and a facility for Knowledge Acquisition which appears as external interface to enable the knowledge engineer to represent the expert knowledge as rules. This facility should provide the knowledge engineer with tools to add, delete and update the rules.

The visitor interacts with the system in indirect way through the dietitian. The dietitian shows the visitor his case details and let him to know the proposed meal plans according to the diagnosis. The feedback of the visitor is entered to the system and the system re-evaluates the visitor choices and gives the dietitian the suitable advice.

A. *Inference Engine*

The inference engine depends on the inference engine for NGES (Nutritional Guidance Expert System) presented by Rokaya, 2014.NGES is an expert system which gives the nutritional guidance for a small portion of nutritional problems. In this system, information guidance consists of the following three kinds of reasoning processes: exclusive reasoning, inclusive reasoning, and reasoning about complications. Rough set theory is introduced in order to describe these algorithms as shown in the next section.

Exclusive Rules: Exclusive rules is equivalent to the necessity condition of a given guidance conclusion. To insure the compactness of exclusive reasoning, the requirements are chosen to be minimal. This means that the attributes should be mapped to a given priority function which determine whether a given attribute will be chosen or not against the priority of the other attributes. Therefore it is intended to formulate induction of exclusive rules based on using the whole given attributes. After the induction, based on the priority function the least requirements for describing exclusive rules are acquired.

Inclusive Rules: Historical information related to known pattern of guidance information forms the base of inclusive rules. This historical information is combined of a set of rules. Based on the related signs of a specific pattern that appears in a given case, the guidance pattern related is recommended with some probability. Dietitians are asked for all recommended guidance patterns to choose the strongest one. Here two measures are used. *SI* (Sufficient Index) and *CI* (Covering Index). *SI* is the probability that a specific guidance pattern can be assigned to a specific case . And, *CI* is the ratio of the cases which satisfy the set to all the cases of this guidance pattern. A positive rule is explained by a set of historical information, *SI* represents the accuracy measure and *CI* represents the total positive rate. It is important to put in mind that *SI* and *CI* are determined empirically by nutritional the dietitians.

Guidance Pattern Image: Using this rule, the historical information is searched for which cannot be explained by the conclusions. This rule is used to determine complications of multiple guidance patterns, acquired from all the possible historical information of the guidance pattern. Those characteristics infer complications of other guidance patterns.

B. *Classification Rules*

Before giving the form of classification rule. Some definitions from rough theory are needed:

Definition 1 (Equivalence Relation) Let U be a universe, and V be a set of values. A total function f from U to V is called an assignment function of an attribute. Then, an equivalence relation R_f is introduced such that for any

$u,v \in U, uR_f v$ iff $f(u) = f(v)$. Secondly, a set of samples which satisfy R_f is denoted by $[x]R_f$. Finally, U which stands for "Universe", denotes all training samples. According to these notations, probabilistic rules are defined as follows:

Definition 2. (Probabilistic Rules) Let R_f be an equivalence relation specified by some assignment function f , D denotes a set whose elements belong to a class d , or positive examples in all training samples (the universe, U . Finally, let $|D|$ denotes the cardinality of D . A probabilistic rule of D is defined as a quadruple, $\left\langle R_f \overset{\alpha,k}{\rightarrow} d, \alpha R_f(D), kR_f(D) \right\rangle$, where $R_f \overset{\alpha,k}{\rightarrow} d$ satisfies the following conditions:

$$[x]R_f \cap D \neq \phi$$

$$\alpha R_f(D) = \frac{|[x]R_f \cap D|}{|[x]R_f|}$$

$$kR_f(D) = \frac{|[x]R_f \cap D|}{|D|}$$

In the above definition, α corresponds to the accuracy measure: if α of a rule is equal to 0.9, then the accuracy is also equal to 0.9. On the other hand, k is a statistical measure of how proportion of D is covered by this rule, that is, a coverage or a true positive rate: when k is equal to 0.5, half of the members of a class belong to the set whose members satisfy that equivalence relation [16].

Based on the above definitions, classification rules are defined as follows:

(1) Exclusive rules $R \overset{\alpha,k}{\rightarrow} d$ s.t. $R = \wedge_i R_i = \wedge \vee_j \lfloor a_j = v_k \rfloor$ and $K_{R_i}(D) = 1.0$.

(2) Inclusive rules:

$R \overset{\alpha,k}{\rightarrow} d$ s.t. $R = \vee_i R_i = \vee \wedge_k \lfloor a_j = v_k \rfloor \alpha_{R_i}(D) > \delta_\alpha$,

and $k_{R_i}(D) > \delta_k$, Note that, induction of inclusive rules produce two problems. First, SI and CI are over fitted to the training samples. Secondly, there are many other rules other than the above one which are induced from the training samples. Therefore some of them should be removed from primary induced rules under some conditions.

Guidance Pattern Image: $R \overset{\alpha,k}{\rightarrow} d$ s.t. $R = \vee R_i \vee \lfloor a_i = v_j \rfloor$ and $\alpha_{R_i}(D) > 0 (k_{R_i}(D) > 0)$. The coverage $k_R(D)$ presents an essential part role in classification of classification rules.

C. *Inductions Rules of NGES*

The components of the induction algorithm are exhaustive search procedure and post processing procedure. The exhaustive search procedure inducesthe pattern image and the exclusive rule for every pattern through all the attribute-value pairs that correspond to selectors in AQ. The post processing procedure induces inclusive rules through the combinations of all the attribute value pairs that correspond to complexes in AQ. For more details see [16]

D. *Database Structure.*

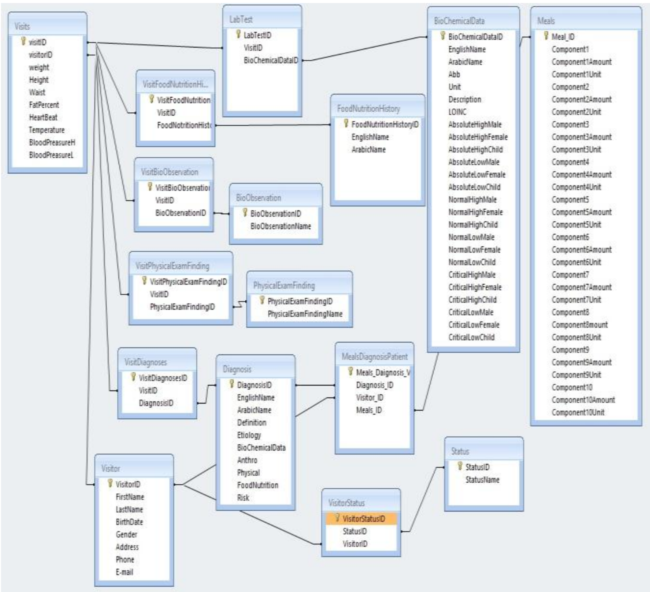

Figure 3. Database Entity Relationship Diagram

As mentioned earlier, Figure 3 illustrates the structure of the database. The system helps dietitians to diagnose, monitor, guide and control the development of the visitor nutritional status. The database depends on the concept of visit. The visitor visit the dietitian and the dietitian save the visitor information and ask him to make necessary biochemical checks at the lab. Through repeated visits, the dietitian can adjust his diagnose. The inference engine helps the dietitian to analyze the enormous information saved historically saved for a given visitor. The system keeps record for each meal in meals table. For a given visitor, Based on the related diagnosis the dietitian can determine the proposed meals. After discussion between the visitor and the dietitian, the dietitian enters the proposed meals to the system for evaluation. Each approved meal is entered to the linking table MealDiagnosisPatient

IV. EXPERIMENTS AND RESULTS

The experiments consist of 2 groups, the first group was done to test the inference engine efficiency and the second group was done to provide a practical trial of using the whole system.

A. *Testing the inference engine efficiency*

In this set of experiments, a verifications of the results performed by [16]was done. The same experiments were done using the same information mentioned in [16].

The data that were used in [16] are: NRIM-REX is applied to the following three nutritional domains: Obesity (NGES domain), whose training samples consist of 220 samples, 10 classes, and 20 attributes, Diabetes, whose training samples consist of 150 samples, 15 classes, and 25 attributes, and Lack of vitamins, whose training samples consists of 200 samples, 3 classes, and 27 attributes. In these experiments, δ_α and δ_k , are set to 0.75 and 0.5, respectively. The experiments are performed by the following four procedures. First, these samples are randomly split into half (new training samples) and half (new test samples). For example, 220 samples are split into

100 training samples and 120 training samples. Secondly, NRIM-REX, AQ15 and CART are applied to the new training samples[16]. Thirdly, the repeated cross validation method and the boot- strap method are applied to the new training samples in order to estimate the accuracy and coverage of NRIM-REX. Finally, the induced results are tested by the new test samples. These procedures are repeated for 100 times and all the estimators are averaged over 100 trials.

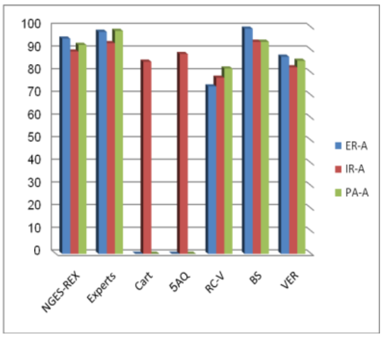

Figure 4. Experimental Results (Obesity)

Experimental results are shown in Figures 4 , 5 and 6. Exclusive rule accuracy (ER-A) means how many training samples that do not belong to a class are excluded correctly from the candidates. Inclusive rule accuracy (IR-A) is equivalent to the averaged classification accuracy. Finally, Pattern image accuracy (PA-A) shows how many signs, which cannot be explained by classification conclusions, are detected by the pattern image. The first row is the results obtained by using NRIM-REX, and the second one is the results derived from nutritional experts. And, for comparison, the classification accuracy of inclusive rules is compared with that of CART and AQ-15, which is shown in the third and fourth row, in the fifth and sixth row, the results of estimation by repeated cross-validation method (R-CV) and the bootstrap method (BS) are presented. Finally, a verification column was added. The verification column shows that the results of [16] were correct but it seem to be higher than current results. These results can be summarized to the following three points. First, the induced rules perform a little worse than those of nutritional experts. Secondly, NRIM-REX method performs a little better than classical empirical learning methods, CART and AQ15. Finally, thirdly, R-CV estimator and BS estimator can be regarded as the lower boundary and the upper boundary of each rule accuracy. Hence the interval of these two estimators can be used as the estimators of accuracy and coverage of each rule.

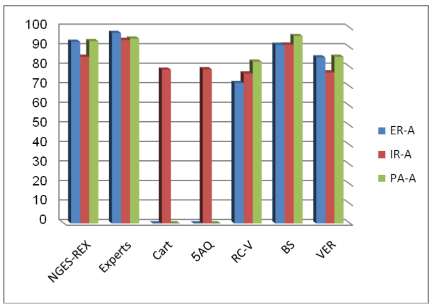

Figure 5. Experimental Results (Lack of vitamins)

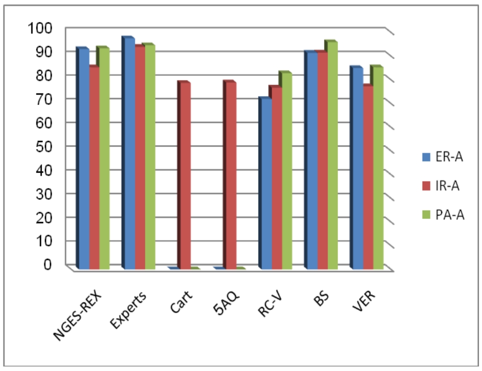

Figure 6. Experimental Results (Diabetes)

B. System Evaluation

In these groups of experiments, the performance of the system was tested in a qualitative bases. A number of famous nutritional diseases had been chosen. Namely, Chronic kidney disease and Protein-Energy Malnutrition (PEM) for hemodialysis patients.The increase in the number of patients with chronic kidney disease has prompted the National Institute of Health to include CKD as a focus area in the Healthy People 2010 initiative [15].According to Devereaux, despite technological advances in dialysis techniques, the mortality rate in the states for dialysis patients is unacceptably high at around 20% per year [15]. PEM is one of the major risk predictor of death for dialysis patients.

10 dietitians were invited to use the system. Each of them was given 10 cases randomly. The dietitian was asked to evaluate the system. They asked to evaluate the speed of the system, flexibility and efficiency. For each parameter the dietitians were asked to give a degree between 1 and 5, where high mark reflects high satisfaction. Also, they were asked to give two marks, one for diagnosis and one for meals evaluation. Table 1 shows the results. In table 1, ***D:*** diagnosis and ***M. E.*** Meal Evaluation

TABLE I. DIETITIANS QUALITATIVE EVALUATION OF THE SYSTEM

	speed		**flexibility**		**efficiency**	
	D	***M. E.***	***D***	***M. E.***	***D***	***M. E.***
Dietitian 1	3	2	2	3	3	3
Dietitian 2	4	5	4	5	5	3
Dietitian 3	5	3	5	3	3	3
Dietitian 3	5	5	4	5	4	2
Dietitian 4	3	3	3	2	4	2
Dietitian 5	5	5	4	4	4	4
Dietitian 6	4	5	3	5	5	2
Dietitian 7	4	5	4	5	3	2
Dietitian 8	3	3	3	3	3	4
Dietitian 9	4	4	4	5	5	3
Dietitian 10	3	3	3	3	3	3
Average	3.9	3.9	3.5	3.9	3.8	2.8

The results shows that a high satisfaction level. The lowest mark was 2.8 for the Meal Evaluation Efficiency. Most of the dietitians reported that the system efficiency is low since for meals evaluation since the visitors themselves has a lack in their abilities to decide which meal component might be suitable for them or not. In most cases they approved what the dietitian decide as in the case of medicine decisions.

V. CONCLUSION

In this research, an expert system was presented depending on rough system theory. It allows professional dietetics to record the data collected from nutritional assessment and perform nutritional diagnosis by evaluating patient's data. Also the system enables the dietitians to decide the proposed meals for each visitor. The visitor with the help of dietitian can modify the meals plan and the system re-evaluate the meals plan to choose the most suitable meal plan. The system is developed through two phases. Training phase, the nutritional information about each case was recorded and the recommended advices regarding diagnosis and corresponding meals lists of real expert are recorded. The expert transforms the crisp information corresponding to each case into non-crisp information. In front of each case the expert add his recommendation in a set of columns; these columns are labeled as expert opinion. From the experiment results, theproposed diagnosis expert system can help dietitians to make their nutritional diagnosis and meal plans more accurate and faster.

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