Vol 2, Issue 2, Apr 2015
Journal of Health Management & Informatics
jhmi.sums.ac.ir
Original Article

A fuzzy logic decision support system for assessing clinical nutritional risk

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Received 2 Dec 2014; Accepted 13 Jan 2015

ABSTRACT

Introduction: Studies have indicated a global high prevalence of hospital malnutrition on admission and during hospitalization. Clinical Nutritional Risk Screen (CNRS) is a way to identify malnutrition and manage nutritional interventions. Several traditional and non-computer based tools have been suggested for screening nutritional risk levels. The present study was an attempt to employ a computer based fuzzy model decision support system as a nutrition-screening tool for inpatients.
Method: This is an applied modeling study. The system architecture was designed based on the fuzzy logic model including input data, inference engine, and output. A clinical nutritionist entered nineteen input variables using a windows-based graphical user interface. The inference engine was involved with knowledge obtained from literature and the construction of 'IF-THEN' rules. The output of the system was stratification of patients into four risk levels from 'No' to 'High' where a number was also allocated to them as a nutritional risk grade. All patients (121 people) admitted during implementing the system participated in testing the model. The classification tests were used to measure the CNRS fuzzy model performance. IBM SPSS version 21 was utilized as a tool for data analysis with $\alpha = 0.05$ as a significance level.
Results: Results showed that sensitivity, specificity, accuracy, and precision of the fuzzy model performance were 91.67% (±4.92), 76% (±7.6), 88.43% (±5.7), and 93.62% (±4.32), respectively. Instant performance on admission and very low probability of mistake in predicting malnutrition risk level may justify using the model in hospitals.
Conclusion: To conclude, the fuzzy model-screening tool is based on multiple nutritional risk factors, having the capability of classifying inpatients into several nutritional risk levels and identifying the level of required nutritional intervention.

Keywords: Clinical decision support system; Fuzzy sets; Intelligent system; Expert system; Nutritional risk assessment

►*Please cite this paper as:*
Hadianfard AM, Abdul Kareem S, Bastani B, Karandish M. A fuzzy logic decision support system for assessing clinical nutritional risk. J Health Man & Info. 2015;2(2):34-40.

Introduction

Nutritional screening as a first step in the nutrition care process is very important because it is not feasible for most hospitals to provide nutritional care for all admitted patients. Therefore, screening is a good way to identify patients who require nutritional care. In addition, it helps clinicians to determine the level of nutritional intervention based on the local policy so that high-risk patients are given more nutritional care compared with low-risk patients (1, 2).

Several tools have been suggested for screening nutritional risk levels (3) such as Mini Nutritional Assessment (MNA) (4), Malnutrition Universal Screening Tool (MUST), and Malnutrition Screening Tool (MST). These tools serve several functions; for example, MNA is used for screening nutritional risks in older people, MUST for screening adults in community (5), and self-screening for screening in outpatient (6). MST has also been suggested for inpatients. These tools are associated with different indicators. For instance, MNA involves six indices (food intake decline, weight loss, acute disease neuropsychology, BMI, and mobility) while MUST uses three indices (BMI, weight loss, and acute disease) and MST is a two-index based tool (weight loss and decreased appetite) (5). Kondrup et al. (2003) suggested another tool for screening nutritional risk called NRS-2002, which is based on the measurement of three indices (BMI, recent weight loss percentage, and changes in food intake) (7). Moreover, the British nutrition-screening tool was used by Mirmiran et al. (2011). It is a questionnaire used to assess the nutrition status of inpatients by nurses. In addition to the usual indices (BMI and weight loss), this tool uses other indices such as triceps skin fold thickness, mid-arm circumference (to estimate the percentage of body fat) and physical activity coefficient (to estimate energy need)

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for screening nutritional risk (7). According to European Society for clinical Nutrition and Metabolism (ESPEN) guideline, the components of a nutritional risk screen are BMI, weight loss, food intake, and severity of current disease (8). Some CNRS tools may also use biochemical indices (5).

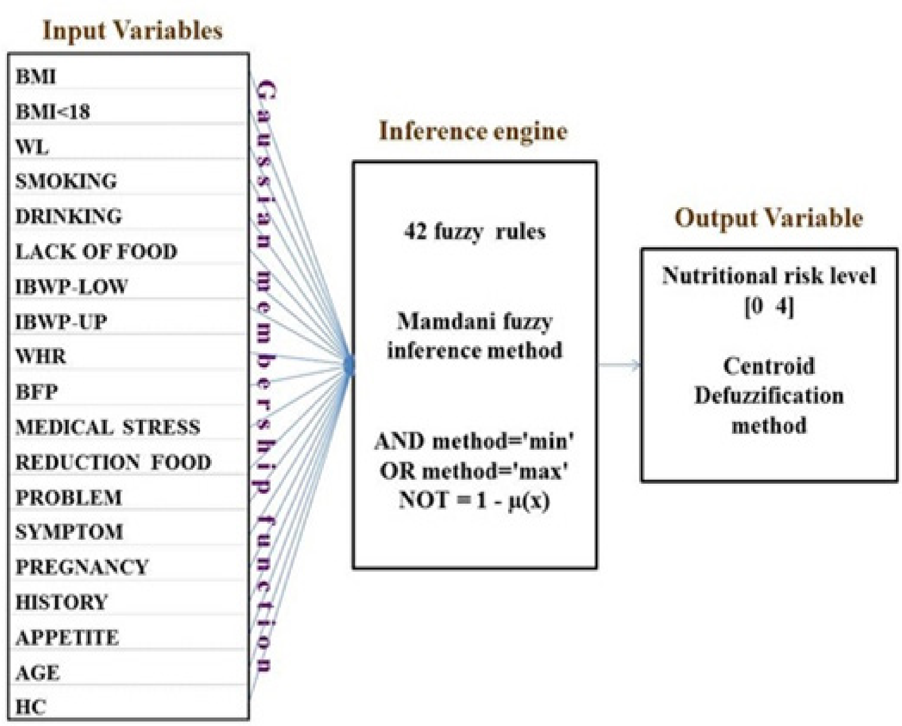
Studies have shown that it is not easy for some hospitals to employ the above mentioned tools in order to assess the nutritional status on admission for all inpatients. For example, some hospitals in Iran (9), Australia (5) and European countries (10) had such a problem. This may be due to the fact that nutritional assessment process is time consuming since it requires some measurements, such as BMI, body fat percentage, and weight loss percentage; also it is necessary to recognize the patient's nutritional status (3). A reliable and easy computerized screening tool that covers uncertain conditions based on fuzzy logic may facilitate screening on a routine basis.

The nature of fuzzy set and the growing use of fuzzy model in the assessment of clinical risks in different fields of medicine (11-15) led this research to employ fuzzy logic as a modeling approach. Fuzzy logic is an approach based on the degree of membership rather than the usual binary value (0 or 1). Defining a fuzzy set for a variable allows one to consider its belonging to the set totally or partially (16). In addition, the fuzzy logic is capable of reasoning in a situation of uncertainty and inadequacy of information (17). Meanwhile, nutritional risk is consistent with a fuzzy set because a person has a degree of risk from health to high risk. A healthy person does not belong to the set while a high-risk person totally belongs to it. A partial blogging can be considered where a person is at low risk. Moreover, when the value of the risk factors is located on the border of health and risk or there is incomplete information about them, a fuzzy set can be used to assign a degree of risk. Therefore, the present study modeled and utilized a computerized decision support system for clinical nutritional risk screening employing fuzzy logic involving multiple risk factors.

Methods

This was an applied modeling study in order to model a Clinical Nutritional Risk Screen (CNRS) and test its performance through implementing. The CNRS model was designed to help clinical nutritionists to identify nutritional status through screening clinical nutritional risks as well as to determine nutritional intervention level and priorities for nutritional care. To this end, the system architecture was designed based on fuzzy logic model to screen clinical nutritional risks. The structure of the system consists of three main components including input data, inference engine, and output (Figure 1). It also included several fuzzy sub-models so that outputs of the fuzzy sub-models were used as the input in the main fuzzy model. The input data were entered by clinical nutritionists through a windows based graphical user interface platform created under Microsoft Visual Studio 2010 using C sharp (C#). Definitions of clinical nutritional risk factors were stored in the knowledge base using Microsoft SQL Server 2005. 'IF-THEN' rules were used as an inference engine. In the output, patients were stratified into four nutritional risk levels from 'No' to 'High' and subsequently graded. MATLAB version 7.12 was used to implement the inference model.

Figure 1. The CNRS fuzzy model



Input variables

Nineteen variables with an influence on the CNRS (1, 3-5, 8, 10, 18, 19) were chosen as the input variables. A clinical nutritionist collected these variables from patient record when patients were admitted. The variables are listed in Table 1.

The value of each input variable obtained from patients was calculated and converted into fuzzy linguistic. In addition, the severity of each factor was defined based on Equation 1.

Table 1. The list of input variables of CNRS fuzzy model

Name	Description	Numerical value (range)	Linguistic value	Collecting method
BMI	body mass index for above 18 years old	11 - 60	underweight, normal, overweight, obese	calculation
WL	body weight loss percentage	0% - 15%	insignificant, significant, severe	calculation
Smoking	smoking status	0 – 20 cigarettes per day	never, light, moderate, heavy	interview
Drinking	drinking habit	0 – 1.5 fl oz. per day	never, light, moderate, heavy	interview
lack of food	lack of food intake from mouth	0 – 7 days	no, mild, moderate, severe	interview
IBWP-low	ideal body weight percentage – lower boundary	60% - 110%	severe malnutrition, moderate malnutrition, mild malnutrition, normal	calculation
IBWP-up	ideal body weight percentage – upper boundary	110% - 210%	overweight, obesity, extreme obesity	calculation
WHR ratio	waist – hip circumference	0 - 3	low, moderate, high	calculation
BFP	body fat percentage	0 - 3	healthy, overweight, obese/under fat	calculation
medical stress	medical stress coefficient	1 -2.5	no, low, medium, high	observation
reduction food	reduction rate in food intake during the last week	0%-100%	no, low, medium, high	interview
Problem	food intake prob-lems	0 - 1	no, yes	Interview, observation
symptom	signs and symptoms related to nutrition deficiency	0 - 1	no, yes	Interview, observation
Pregnancy	pregnancy status	0 - 1	no, yes	interview
History	history of diseases related to nutrition that is still	0 - 1	no, yes	interview
appetite	appetite status	0 - 1	usual, less/more than usual	interview
Age	Age	0 – 100 years	young & middle-age, old-age	interview
BMI<18	body mass index for under 18 years old	0 - 3	normal, underweight/over-weight, malnutrition/obesity	calculation
HC	head circumference	0 – 1	normal, big/small size	measurement

$$severity = f(x) = \frac{a-x}{a-b} + s \quad (1)$$

Where
$0 \leq f(x) \leq 4$
$a \leq x \leq b$
a is the lower boundary and b is the upper boundary of
$1 \leq s \leq 3$; s is the score assigned to different value ranges of each input variable. They are summarized in Table 2
for $x = a$; $f(x) = s$
for $x = b$; $f(x) = 1 + s$

The Gaussian curve membership function was employed to determine the degree of membership (Equation 2).

$$\mu(x) = Gaussian(x, c, \sigma) = e^{\frac{-(x-c)^2}{2\sigma^2}} \quad (2)$$

Where
$0 \leq \mu(x) \leq 1$
$\sigma > 0$ and $e \approx 2.718281828$
C and σ are the center and the width of the Gaussian curve, respectively.

Table 2. The score of nutritional risk factors (input variable)

Score 3	Lack of food intake from mouth for over 5 days Addiction and Alcoholism (heavy) IBW% > 200 or < 70 Weight loss in 3-6 months > 10% Medical stress coefficient > 1.5 Reduced rate in food intake during the last week >75% BMI > 30 or < 18.5 Waist to hip ratio > 1 for male and > 0.85 for female Low or high body fat percentage Small or large head circumference for age < 5 yrs.
Score 2	Lack of food intake from mouth for 3-5 days Medium use of drugs and alcohol IBW% = 130-200 or 70-80 Weight loss in 3-6 months = 10% Medical stress coefficient = 1.3–1.5 Reduced rate in food intake during the last week=50%-75% BMI = 25-30 Waist to hip ratio = 0.95-1 for male or 0.8-0.85 for female Overweight based on body fat percentage Food intake problems such as difficulty chewing and swallowing Signs and symptoms related to nutritional deficiency Pregnancy
Score 1	Lack of food intake from mouth for 1-3 days Little use of drugs and alcohol IBW%=110-130 or 80-90 Weight loss in 3-6 months < 10% Medical stress coefficient < 1.3 Reduced rate in food intake during the last week=25%-50% History of diseases related to nutrition that is still Changing in appetite (less or more than usual) Age > 70

(1, 4, 5, 7, 8, 10, 18-20)

Inference engine

The inference engine of the CNRS fuzzy model contained 42 fuzzy rules. All rules had the same weight and were equated to one. The Mamdani fuzzy inference method (20) was used to infer the nutritional risk level. The fuzzy operation intersection (AND) was equated to the 'Min' function and the fuzzy union (OR) equated to the 'Max' function. The fuzzy complement (NOT) operation was also used in the antecedents (Figure 1).

Output

The CNRS fuzzy model had one output, namely nutritional risk level. It was categorized into four levels including no risk, low risk, medium risk, and high risk (Table 3). The centroid defuzzification method was used to return the linguistic fuzzy variable to a crisp number between 0 and 4 (Figure 1).

In addition to nutritional risk level, the grade of severity, which indicates the sum of the severity of risk factors, was determined. The severity of each factor was calculated according to equation 1 and the grade was calculated from equation 3. For example, for a patient who has been admitted to the hospital with two clinical nutritional risk factors; 1) the patient has lost about 13% of weight during the previous 6 months and; 2) he/she has lost appetite. The grade of severity of the patient is calculated in the following way: Grade = (severity of weight loss) + (severity of lost appetite)

Table 3. The values of nutritional risk level as the output

Linguistic value	Numerical value
No	0 -1
Low	1 -2
Medium	2 - 3
High	3 - 4

$$Grade = \sum_{i=1}^{19} (severity)_i$$

The grade allows us to choose a better priority for patients who require nutritional care, especially when they are in the same risk level and hospital services are limited. For instance, in a situation in which there would be two patients with the same medium risk but two different grades of 2 and 3, the patient with grade 3 will be given higher priority for nutritional care.

Testing

To evaluate the performance of the CNRS fuzzy model, the system was implemented at four selected wards (Endocrine, Internal medicine, Pediatrics, and Orthopedics) of two Iranian principal teaching hospitals (Namazi and Golestan) for four months. Those wards were chosen based on their degree of involvement in nutrition. For example, patients who are admitted to the endocrine ward have usually nutrition related diseases, like Diabetes Mellitus. On the other hand, patients hospitalized in the orthopedics ward are usually due to injuries and fractures. This system was applied to all 121 patients (The average length of stay: 4.67 days; SD = 2.16) admitted to aforementioned wards during the implementation. Manual assessment was also performed separately by two clinical nutritionists and considered as a comparative standard. Classification tests including Sensitivity, Specificity, Accuracy, and Precision were used to measure the CNRS fuzzy model performance and one way ANOVA was applied to compare the results of wards. A value of $\alpha = 0.05$ was considered as the significance level. IBM SPSS version 21 was utilized as a tool for data analysis.

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Results

According to assessments of two clinical nutritionists, 25 out of 121 patients were not at nutritional risk while 96 patients were. However, the CNRS fuzzy model could detect 94 patients with nutritional risk and 27 patients not at risk. Table 4 shows the number of admitted patients to the four wards, which were classified as positive, or negative by the CNRS fuzzy model.

Table 4. The results of applying the CNRS fuzzy model by ward

Ward	The CNRS fuzzy model	Actual nutritional risk*		Total
		Yes	No	
Endocrine	Positive	18	0	18
	Negative	1	0	1
	Total	19	0	19
Internal medicine	Positive	20	2	22
	Negative	2	5	7
	Total	22	7	29
Pediatrics	Positive	33	1	34
	Negative	3	2	5
	Total	36	3	39
Orthopedics	Positive	17	3	20
	Negative	2	12	14
	Total	19	15	34
Total	Positive	88	6	94
	Negative	8	19	27
	Total	96	25	121

* Based on the clinical nutritionists assessment

The results of the CNRS fuzzy model performance are presented in Table 5. The capability of the CNRS fuzzy model for screening patients with nutritional risk was 91.67% (±4.92; α =0.05); sensitivity, specificity, accuracy, and precision of the fuzzy model performance were 76% (±7.6; $\alpha = 0.05$), 88.43% (±5.7; $\alpha = 0.05$), and 93.62% (±4.32; $\alpha = 0.05$), respectively. In addition, the results showed a statistically significant difference ($F = 6.581$; df = 3, 117; $p < 0.001$) between the wards. The endocrine ward had the largest sensitivity (94.74%) while the orthopedics ward had the smallest sensitivity (89.47%) and the largest specificity (80%).

As shown in Table 5, some tests like specificity could not be calculated for the endocrine ward as patients admitted in this ward are usually at nutritional risk because of their clinical condition and nature of the disease. In this case, all admitted patients in the endocrine ward were at risk (Table 4).

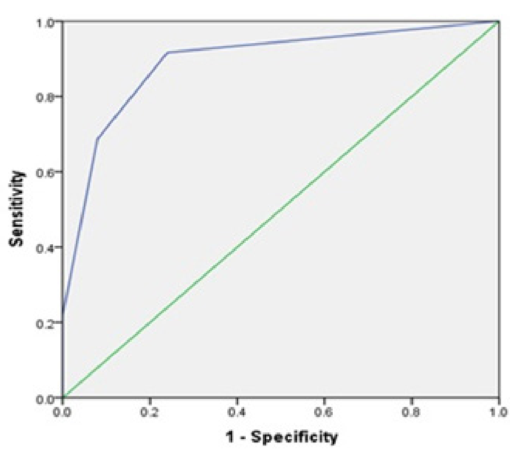
Receiver Operating Characteristic (ROC) curve, which is a plot of sensitivity (true positive rate) versus 1- specificity (false positive rate), was used to demonstrate the model's detection threshold. Figure 2 indicates that the area under the curve was 0.893 (CI = 0.823 – 0.962; $\alpha = 0.05$; $p < 0.001$).

Table 5. The classification test result of CNRS fuzzy model

Ward	Sensitivity	Specificity	Accuracy	Precision	NPV	LR +	LR -
Endocrine	94.74%	-	94.74%	100%	-	-	-
Internal medicine	90.91%	71.43%	86.21%	90.91%	71.43%	3.18	0.1272
Pediatrics	91.67%	66.67%	89.74%	97.06%	40%	2.75	0.1249
Orthopedics	89.47%	80%	85.29%	85%	85.71%	4.47	0.1316
Total	91.67%	76%	88.43%	93.62%	70.37%	3.82	0.1096

NPV: Negative Predictive Value
LR +: Likelihood Ratio positive
LR -: Likelihood Ratio Negative

Figure 2. ROC curve for demonstrating the diagnostic performance of the CNRS fuzzy model



Discussion

This study explored the use of a prototype computer-based clinical decision support system based on the fuzzy logic to help clinicians for clinical nutrition screening and stratifying patients into four nutritional risk levels of normal, low risk, medium risk, and high risk.

To the best of our knowledge and based on our research, there is no similar study to rank patients according to severity of risk factors. This study applied a new index called 'Grade'. The grade ranks patients based on the severity of risk factors. It helps clinicians to improve their decision regarding priority and level of nutritional interventions performed, especially when patients are in the same risk level. In a similar way, Kong et al. made use of the interval score in addition to the overall risk scores to obtain further information in order to treat patients if they are at the same risk level (22) .

In addition, the present study employed multiple risk factors (19 input variables) to identify nutritional risk levels while the other studies (3-5, 7, 8, 10, 18, 19) used about 2 to 6 risk factors for nutritional risk screening.

Using multiple factors can increase the chance of recognizing patients who are at risk and improve patients' ranking on different risk levels. The CNRS fuzzy model had a good performance in detecting patients who were at risk. Moreover, it helped to determine the priority and intervention level for providing nutritional care (sensitivity 91.67% and specificity 76%).

Limitation

The number of wards and the running time were limited in this study as it was difficult and time consuming to coordinate the implementation of the system with hospitals, wards and medical practitioners. In addition, it was difficult to obtain the agreement of hospitals to run the system since applying such a system caused some changes in the daily routines of the wards.

Implication

The CNRS fuzzy model can be used as a routine task to carry out nutritional status assessment in hospitals. This model may help clinicians to assess nutritional status easier, faster, and more reliably and increase the rate of screening. Consequently, patients who are at risk and need nutritional intervention will be identified and provided with required treatment. Subsequently, this may result in enhancing the quality of care as the final consequence of the application of the CNRS fuzzy model.

Conclusion

This research indicated that fuzzy logic can be used for a specific purpose in modeling clinical nutritional screen based on the general capability. Therefore, CDSSs based on fuzzy logic can be considered as a screening and supportive tool for diagnosis of nutritional status in order to improve patient care. This system can be used in all hospitals and for all inpatients on admission by clinical nutritionists.

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Contributors

All the authors provided substantial contributions to conception or design, acquisition of data or analysis and interpretation of data. They assisted in drafting the article or revising it critically for important intellectual content. They provided final approval of the version to be published.

Acknowledgment

This research was supported by a grant from the Health Research Institute, Diabetes Research Center of Ahvaz Jundishapour University of Medical Sciences (AJUMS), grant no. D-8805 and University of Malaya with grant number PS402-2010B.

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