An Intelligent Decision Support System (IDSS) for Nutrition Therapy: Infrastructure, Decision Support, and Knowledge Management Design

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ABSTRACT

In this paper, the authors have presented an expert system to support decision makers in nutrition therapy planning. This system is an extended version of a fuzzy decision support system for nutrition therapy. The presented expert system is equipped with an updated knowledge base component by using a set of rules. Also in order to deal with vagueness and uncertainty, fuzzy set theory could provide a suitable framework for data management, modelling and decision support. Therefore, fuzzy rules empower this system to be implemented more realistically. In addition, for developing knowledge management component, artificial neural network (ANN) is applied to survey the input data and information in the long term. The integration of ANN with the expert system provides the possibility for a set of novel rules to be generated and consequently adds new knowledge to the system.

Keywords: *Artificial Neural Network, Expert Systems, Fuzzy Logic, Intelligent Decision Support Systems, Knowledge Management, Multi-Criteria Decision Making, Nutrition Therapy, Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)*

INTRODUCTION

Nutrition therapy is a science-based, yet holistic approach to nutritional counseling rooted in the conviction that food is a form of medicine that can heal, protect, nurture and support good health. Food provides energy and building materials for countless substances that are essential for the growth and survival of every human being (Mahan, Escott-Stump, & Raymond, 2012). Macronutrients[1] contribute the total required energy, but ultimately the energy they

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yield is available for the work of the muscles and organs of the body. Release of energy for the synthesis, movement, and other functions requires the micronutrients[2] which function as coenzymes, co-catalyst, and buffers in the miraculous, watery arena of metabolism. States of nutritional deficiency or excess occur when nutrient intake does not match an individual's requirements for optimal health, and we have to keep balance of nutrient intake and nutrient requirements (Mahan, Escott-Stump, & Raymond, 2012).

Decision making is a process of choosing among alternative courses of action for the purpose of attaining a goal or goals (Turban & Aronson & Liang, 2007; Turban & Volonino, 2010; Laudon & Laudon, 2012). Decision making is a prestigious scientific, social, and economic endeavor. Therefore, a decision making situation involves partial, incomplete, or inexact information. A decision support system (DSS) is defined as "interactive computer-based system, which helps decision makers utilize data and models to solve unstructured problems" (Gorry & Scott Morton, 1971). In some decision situations, the support offered by data and model management alone may not be sufficient. Expert systems (ES) provide additional support to substitute for human expertise through supplying the necessary knowledge; however, several other intelligent technologies can be used to support decision situations that require expertise (Turban & Aronson & Liang, 2007). ES are influential systems that assist decision making and apply in a variety of problem domains (Buchanan & Smith, 2003).

Thus, decision makers use their experiences to handle difficult situations, or in complex decisions, it often turns to experts for advice. They recall similar experiences and learn from them what to do with similar new situations for which exact replicas are unavailable. When this approach to problem-solving is computerized, we call it machine learning, and its primary tools are artificial neural networks (ANN) (Turban, Aronson, & Liang, 2007).

The concept of how neurons work in the human brain is utilized in performing computations on computers artificially. Researchers felt that the neurons are responsible for the human capacity to learn, and it is in this sense that the physical structure is being emulated by a neural network to accomplish machine learning. Each computational unit computes some function of inputs and passes the result to connect units in the network. Accordingly, newly learnt information as a produced knowledge of the system comes out of the entire network of the neurons (Ross, 2004; Turban, Aronson, & Liang, 2007).

Researchers usually combine fuzzy logic methods with other artificial intelligence (AI) methods, such as ES and ANN, to boost their accuracy in decision making process (Turban, Aronson, & Liang, 2007). Therefore, in this paper, we establish fuzzy logic to deal with inexact, incomplete and overall uncertainty of human experiences.

Our programming language for this intelligent decision support system (IDSS) was Visual C# developed by Microsoft. C# is an event driven, object oriented, and visual programming language (Chen, Hsu, Liu, & Yang, 2012).

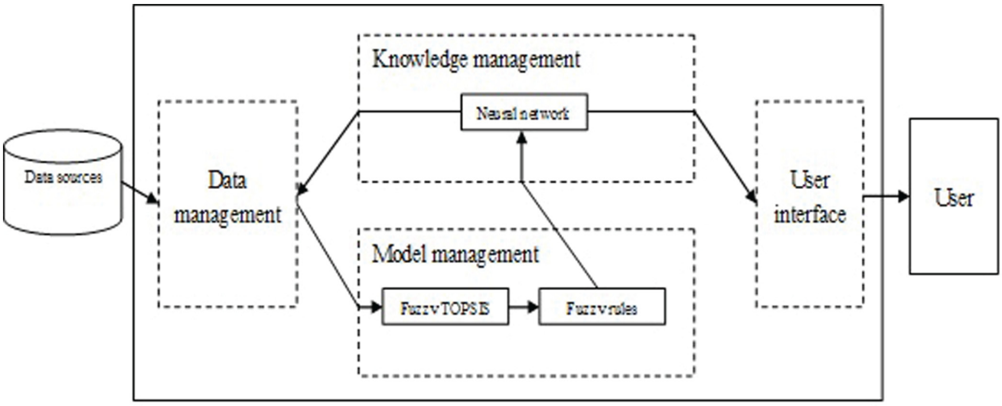
METHODS

Presented IDSS for nutrition therapy has two main parts: (1) decision support system, (2) and intelligent part. The decision support part encompasses attributes, constraints, and alternatives. Also a set of fuzzy rules and a learning feature using ANN form the intelligent part. Below, is a short description about decision support performance and the next segment is about intelligent knowledge base part, it is also illustrated in Figure 1.

Decision Support System

In this part of our system, we implement multi attribute decision making (MADM) methods which are a kind of multi criteria decision making (MCDM) methods. Attributes are the char-

Figure 1. IDSS structure



acteristics, qualities, or performance parameters of alternatives. An MADM problem involves the selection of the best alternative from a pool of pre-selected alternatives described in terms of their attributes (Lu, 2007). Hence, our attributes are a vast collection of foods (alternatives) that should be selected by a well-ordered approach. We establish technique for order preference by similarity to an ideal solution (TOPSIS) to deal with this large amount of data. TOPSIS is a widely accepted MADM technique which is based on the concept that the ideal alternative has the best level of all attributes considered, whereas the negative-ideal is the one with all the worst attribute values (Yong, 2006).

We create the constraints through triangular fuzzy numbers which consist of three values as bounds. Upper bound is the maximum tolerable amount of each nutrient. The lower bound is the minimum recommended amount of each nutrient. Then, we estimate the mean amount by calculation of average needed amount of each nutrient (Fahmi, 2012). Then we extract these bounds from DRI table indicating the appropriate volume of nutrient for individuals regarding particular age, sex, and special subjects for women.

The alternatives are a collection of species of foods that are common around the world. In order to facilitate the application of these data, a data mart which is a subset of the data warehouse has to be created by the decision making through selecting favourite foods (Turban, Aronson, & Liang, 2007).

To implement the first part of decision support, we perform the initialization procedure through defining several lists to save the user's personal information. Then in the next phase, we apply the fuzzy TOPSIS method to contribute optimization steps. Hwang and Yoon (1981) developed the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method (Hwang & Yoon, 1981). Later in 1992, Chen and Hwang developed the fuzzy TOPSIS method that can be implemented like TOPSIS but by fuzzy calculation (Chen & Hwang, 1992).

Also, we constitute a set of alternatives for each decision maker by comparing the amount of all intake nutrients and required amounts of nutrients according to the decision maker's personal situation. Then we will compare obtained alternatives from fuzzy TOPSIS and the existing data in our data mart. Finally, according to ranking value of fuzzy TOPSIS, the system will provide the recommendations.

Intelligent

1. Knowledge management (KM) and knowledge management systems (KMS)

Knowledge is a broad concept from data and information in the information technology context. KM is a process that helps organizations identify, select, organize, disseminate, and transfer important information and expertise (Turban & Aronson & Liang, 2007). According to Alavi and Leidner (1998), KMS refer to the use of modern information technologies to systematize, enhance, and expedite KM. KMS attempt to capture knowledge before people leave (Beazley, Boenisch, & Harden, 2002; Kurtzman, 2003; Lesser & Prusak, 2001).

DSS typically involves running models to support decision makers and solve problems. This is not typically done by KMS. However, since a KMS provides help in solving problems by applying knowledge, part of the solution may involve running models. KMS can integrate into a set of models and data, and can activate them if a specific problem calls for it:

2. AI

AI methods and tools could implement in KMS practically. They can assist in identifying expertise, eliciting knowledge automatically and semi-automatically. AI methods, notably ES, neural networks, and fuzzy logic are used in KM. KMS are expected to enhance the quality of support provided to decision-makers, support KM functions such as acquisition, creation, exploitation, and accumulation, facilitate discovery of trends and patterns in the accumulated knowledge (Nonaka, 1995):

3. ES

An ES is a software program which helps solve problems with expert-level solutions and is heuristic, transparent and flexible. It reasons with human experts' domain knowledge while providing explanations of how it reaches the conclusion and is flexible so that it can easily add or update the existing knowledge (Buchanan & Smith, 2003). ES is a branch of applied AI developed in the middle of 1960. The principle behind an ES is basically transferring the expertise from humans to computer. ES could aid non-experts to perform better instead of replacing the experts entirely. One of the purposes of ES is to make expert's knowledge and experience more widely available (Turban, Aronson, & Liang 2007). Expertise from human would be stored in a database, and when the knowledge is needed, users or programs could easily retrieve the knowledge stored in the database when needed. ES should be able to make inferences and comes to a conclusion. Much like a human expert, the ES should have the capability to explain the logic that it uses in order to come up with a conclusion (Turban, Aronson, & Liang, 2007). ES are computer-based information systems that use expert knowledge to attain high-level decision performance in a narrow problem domain (Turban, Aronson, & Liang, 2007).

In the early 1950s, the development of computer software began with a focus in numerical systems. People began rapidly relying on computers to deal with data process at the beginning of 1970s. Stanford University developed a rule-based ES called MYCIN back in 1970s. Although the system is invented almost some 40 years ago, it is still the representative of the state-of-the-art ES. MYCIN was developed to help diagnose the likely cause of patients' infection and provides suggested therapy for patients. Its rule base consists of 450 rules and one thousand facts of medicine regarding to meningitis infections. The system was successful, and it proved that with a rather simple representation of rules in a form of if-then-else statements is enough to handle with a rather complicated but focused domain area such as meningitis infection diagnosis. However, due to some political issues, MYCIN was never put to use in a clinical setting. It was only used for learning and training purposes (Buchanan & Duda, 1982). It is after the successful development of MYCIN, ES technology began to see a light of commercialization. During 1980s, researchers began research AI. United States, Japan, as well as many countries in Europe, began investing in the area of AI and ES, and during this time, many ES tools begin to emerge. The purpose of AI is to broaden the application of computers not only to include numerical calculations but also to possess knowledge and, therefore, enhance the utilization of computers. The major research area for AI includes natural language processing, symbol processing, rule-based system and logic systems (Chen, Hsu, Liu, & Yang, 2012).

The computer program will then make inferences to these rules to the data in order to reach a suitable conclusion. Rule-based ES is utilized in many different domain areas (Shu-Hsien, 2005) and also in medical diagnosis.

According to Turban, Aronson and Liang (2007), AI is the branch of computer science dealing primarily with symbolic, non-algorithmic methods of problem-solving. This definition focuses on two characteristics:

- Numeric versus symbolic;
- Algorithmic versus heuristic.

People tend to think symbolically; our intelligence seems to be based in part on our mental ability to manipulate symbols rather than just numbers. In addition, algorithmic means a step-by-step procedure that has well-defined starting and ending points and is guaranteed to find a solution to a specific problem. Heuristics consists of intuitive knowledge, or rules of thumb, learned from experience (Turban, Aronson, & Liang, 2007).

Learning is an important feature of human computational abilities. Learning may be viewed as the change in behavior acquired due to practice or experience, and it lasts for a relatively long time (Ibrahim, 2004). AI systems do not have the same learning capabilities that humans have, but they do have mechanical learning capabilities, called machine learning, that allow the system to adjust its behavior and react to changes in the outside environment.

Many organizations use neural networks to automate complex decision-making. Neural networks can readily identify patterns from which they generate a recommended course of action. As such networks learn from experience to improve the performance of machine, they are members of a technology family called machine learning (Turban, Aronson, & Liang, 2007):

4. Expert and knowledge engineers

An expert has special knowledge, judgment, experience, and methods, along with the ability to apply these talents to give advice and solve problems. It is the expert's job to provide knowledge about how to perform the task that the knowledge based system will perform.

Knowledge engineers collect and organize knowledge gathered from domain expert then convert the expert knowledge into a form which a computer ES understand and save converted knowledge into the knowledge base. Users enter the collected facts into the system via the user interface and save the data into the fact base. Finally, users get the results, recommendations and explanations from the system:

5. Knowledge base

The knowledge base contains the relevant knowledge necessary for understanding, formulating, and solving problems. It includes two basic elements: (1) facts, such as the problem situation and the theory of the problem area, and (2) special heuristics or rules that direct the use of knowledge to solve specific problems in a particular domain. In addition, the inference engine can include general purpose of problem solving and decision-making rules (Turban, Aronson, & Liang, 2007).

EQUATIONS AND RULES

1. Constraints

Constraints are like limitations for decision making problems. Thus, in this paper we establish a set of fuzzy constraints for the fuzzy TOPSIS method. A fuzzy number $\tilde{S}$ is a fuzzy set which the membership function is $\mu_{\tilde{S}} : R \rightarrow [0,1]$. A triangular fuzzy number

$\tilde{S} = (l, m, u)$ can conform to the characteristics that are depicted in Figure 2. The value *u* treats as an optimistic estimate, intended to be the unlikely but possible value if everything goes well. The value *m* is the most likely estimate, intended to be the most realistic value. The value *l* is a pessimistic estimate, intended to be the unlikely but possible value if everything goes badly. The membership function of $\tilde{S}$ is expressed as (Lin & Hsieh, 2004):

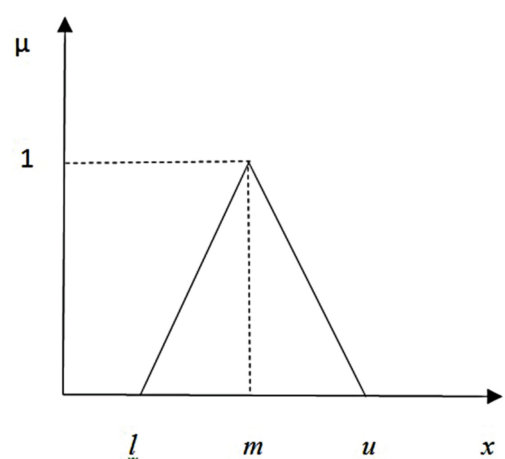
$$\mu_{\tilde{S}}(x) = \begin{cases} \dfrac{(x-1)}{m-1}, & 1 \leq x < m \\ \dfrac{(x-u)}{m-u}, & m \leq x < u \\ 0, & others \end{cases}$$

As mentioned above, we create the constraints by triangular fuzzy numbers consisting of three values as bounds. Upper bound is the maximum tolerable amount of each nutrient. The lower bound is the minimum recommended amount of each nutrient. The mean amount is the estimated average amount of each nutrient. We extract these bounds from the DRI tables which indicate the appropriate volume of nutrient for individuals regarding particular age, sex, and special subjects for women (Mahan, Escott-Stump, & Raymond, 2012):

2. Fuzzy TOPSIS equations

Fuzzy TOPSIS method assesses the alternatives according to received data regarding the amount of intake foods during a day. Fuzzy TOPSIS is based on the concept that the ideal alternative has the best level of all attributes considered, whereas the negative-ideal is the one with all the worst attribute values (Yong, 2006). It defines solutions as the points that are simultaneously farthest from the negative-ideal point and closer to the ideal point. TOPSIS also provides an understandable structure and an adaptable model calculation procedure. TOPSIS has the ability of taking various criteria with different units into account simultaneously. In fuzzy TOPSIS, qualitative data can be converted to fuzzy numbers, which are then used in the calculations (Chen, 2000; Önüt & Soner, 2008). For the determination of the weights of

Figure 2. Triangular fuzzy number



TOPSIS criteria, entropy technique can be used (Asgarpour, 2009). The steps of fuzzy TOPSIS are presented below:

Step 1: Identifying the evaluation criteria:

$$\tilde{x} = \left(a_{ij}, b_{ij}, c_{ij}\right) \forall i, j \tag{1}$$

$$C_1 \ C_2 \cdots C_n$$

$$\tilde{D} = \begin{bmatrix} A_1 & \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ A_2 & \tilde{x}_{21} & \tilde{x}_{22} & \vdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ A_m & \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{2}$$

Step 2: Calculate the normalized fuzzy decision matrix $\tilde{R}$ as:

$$\tilde{R} = \left[\tilde{r}_{ij}\right] \tag{3}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), j \in B$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c_{ij}}\right), j \in C$$

$$c_j^* = \max_i C_{ij} \ \text{ if } j \in B$$

$$a_{\bar{j}} = \min_i a_{ij} \ \text{ if } j \in C$$

B and C are the set of benefit criteria and the set of cost criteria, respectively (Chen & Hwang, 1992):

Step 3: Asgarpour's (2009) identifying the weights of the criteria using entropy technique:

$$\tilde{P}_{ij} = \frac{\tilde{r}_{ij}}{\sum_{i=1}^{m} \tilde{r}_{ij}} \forall i, j \tag{4}$$

$$\tilde{E}_j = -k \sum_{i=1}^{m} \left(\tilde{P}_{ij} Ln \tilde{P}_{ij}\right) \forall j \tag{5}$$

where:

$$k = \frac{1}{Ln(m)}$$

$$\tilde{d}'_j = 1 - \tilde{E}_j \tag{6}$$

$$\tilde{W}_j = \frac{\tilde{d}_j}{\sum_{j=1}^{n} \tilde{d}_j} \forall j \tag{7}$$

$$\tilde{W} = \left[\tilde{w}_1 \ \tilde{w}_2 \cdots \tilde{w}_n\right]$$

$$\tilde{w}_j = \left(w_{j1}, \mathrm{w}_{j2}, w_{j3}\right) \forall j = 1, 2, \ldots, n$$

Step 4: Calculate the weighted normalised fuzzy decision matrix $\tilde{V}$ as:

$$\tilde{V} = \left[\tilde{v}_{ij}\right] \tag{8}$$

$$\tilde{v}_{ij} = \tilde{r}_{ij} \cdot \tilde{w}_j \tag{9}$$

Step 5: Identify the fuzzy positive-ideal solution (FPIS, $\widetilde{A^*}$) and the fuzzy negative-ideal solution (FNIS, $\widetilde{A^-}$):

$$\tilde{A}^* = \left(\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*\right) \tag{10}$$

$$\tilde{A}^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^*\right) \tag{11}$$

where:

$$\tilde{v}_j^* = (1,1,1), \tilde{v}_j^* = (0,0,0)$$
$$\forall j = 1, 2, \ldots, n$$

Step 6: Calculate distances of each alternative from $\widetilde{A^*}, \widetilde{A^-}$

$$d_i^* = \sum_{j=1}^{n} d\left(\tilde{V}_{ij}, \tilde{V}_j^*\right),\ \forall i = 1,2,\ldots,m \qquad (12)$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right),\ \forall i = 1,2,\ldots,m \qquad (13)$$

where $d(\ldots)$ is the distance measurement between two fuzzy numbers:

Step 7: Calculate the closeness coefficient of each alternative a:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}\ \forall i = 1,2,\ldots,m \qquad (14)$$

Step 8: Rank alternatives according to the values of CC_i in descending order and choose an alternative with the maximum CC_i:

3. Fuzzy rules

There are many commercial rule-based ES, because the technology of rule-based systems is well-developed and the development tools can be used by end users. In such systems, a series of rules represents the embedded knowledge in the system (Turban & Aronson & Liang, 2007). In the field of AI (machine intelligence), there are various ways to represent knowledge. Perhaps the most common way to represent human knowledge is to form it into natural language expressions of the type 2 IF premise (antecedent), THEN conclusion (consequent). This expression is commonly referred to as the IF–THEN rule-based form; this form generally is referred to as the deductive form. It typically expresses an inference such that if we know a fact (premise, hypothesis, antecedent), then we can infer, or derive, another fact called a conclusion (consequent) (Ross, 2004):

<Rule>: IF <conditions> THEN <conclusion>

In the presented knowledge base system, we apply a set of fuzzy rules to monitor the energy balance by calculation of energy input and energy requirements. For this purpose, our system asks personal information such as weight, height, and daily walking distance. Then by utilizing these data, we compute body mass index (BMI) and physical activity level (PAL) for each decision maker. According to personal BMI and PAL, we obtain an interval for energy (Mahan, Escott-Stump, & Raymond, 2012). This interval indicates an accepted limitation area as a daily standard recommended amount for energy:

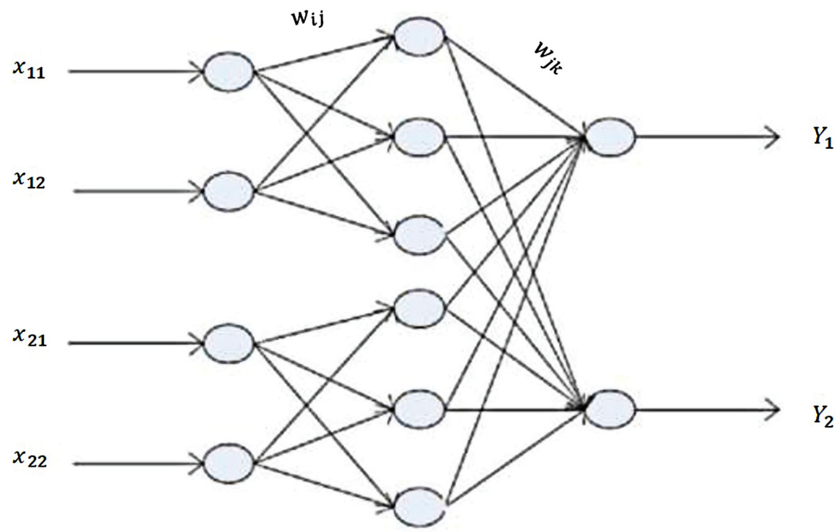
<Rule>: IF <BMI > & IF <PAL > THEN <Energy determination>

4. Neural network

Our ANN system consists of an input layer, a hidden layer, and an output layer. We divide the neural network into single variable neural networks and multi-variable control system. This study focuses on two-input, two-output system. The structure of our neural network is shown in Figure 3.

The network has three layers including input layer, a hidden layer, and output layer. x_{11} is the height of the user, x_{12} is weight, x_{21} is PAL, and x_{22} is the amount of energy the person intake. Our system calculates Y_1 as the fittest energy the person should get from the foods, and Y_2 as the fittest BMI properties. Also w_{ij}, w_{jk} are the weights of the network. The system calculates the amount of input and output layers as follows:

Figure 3. Neural network structure



1. Input layer contains four neurons, output data is equal to the input data, calculated as:

$$x_{si}\left(k\right) = X_{si}\left(k\right) \quad (15)$$

2. There are six hidden layer neurons, including three proportion neurons, three integral neurons and three differential neurons. The neuron input value is the same, calculated as:

$$Net_{sj}\left(k\right) = \sum_{i=1}^{2} w_{ij} x_{si}\left(k\right) \quad (16)$$

$$w_{13} = w_{2,3} = w_{31} = w_{32} = 0,$$
$$w_{11} = w_{21} = w_{22} = w_{33} = 1$$

The system calculates each hidden layer neuron output as the proportion of neurons:

3. Output Layer has two neurons and is calculated as follows:

$$y_h\left(k\right) = \sum_{s=1}^{2}\sum_{j=1}^{3} w_{jk} u_{sj}\left(k\right) \quad (17)$$

In this equation, h is the output layer neuron number, s is a subnet number, j and means the subnet number of hidden layers and w_{jk} is the weight of hidden layer.

INTELLIGENT DECISION SUPPORT SYSTEM (IDSS)

This DSS has been used and examined by a number of researchers and professors in different universities of Iran such as Tarbiat Modares University, University of Tabriz, and Tabriz University of Medical Science. We have presented an example for an objective person by a virtual version of IDSS (Figure 5, Figure 6, Figure 7, and Figure 8). The structure of our IDSS encompasses four modules i.e., (1) decision information module, (2) favourite food module, (3) daily food module, and (4) result module, as illustrated by Figure 4.

CONCLUSION

Energy is the most important nutrition indicator. Energy must be supplied regularly to meet needs

Figure 4. IDSS flowchart

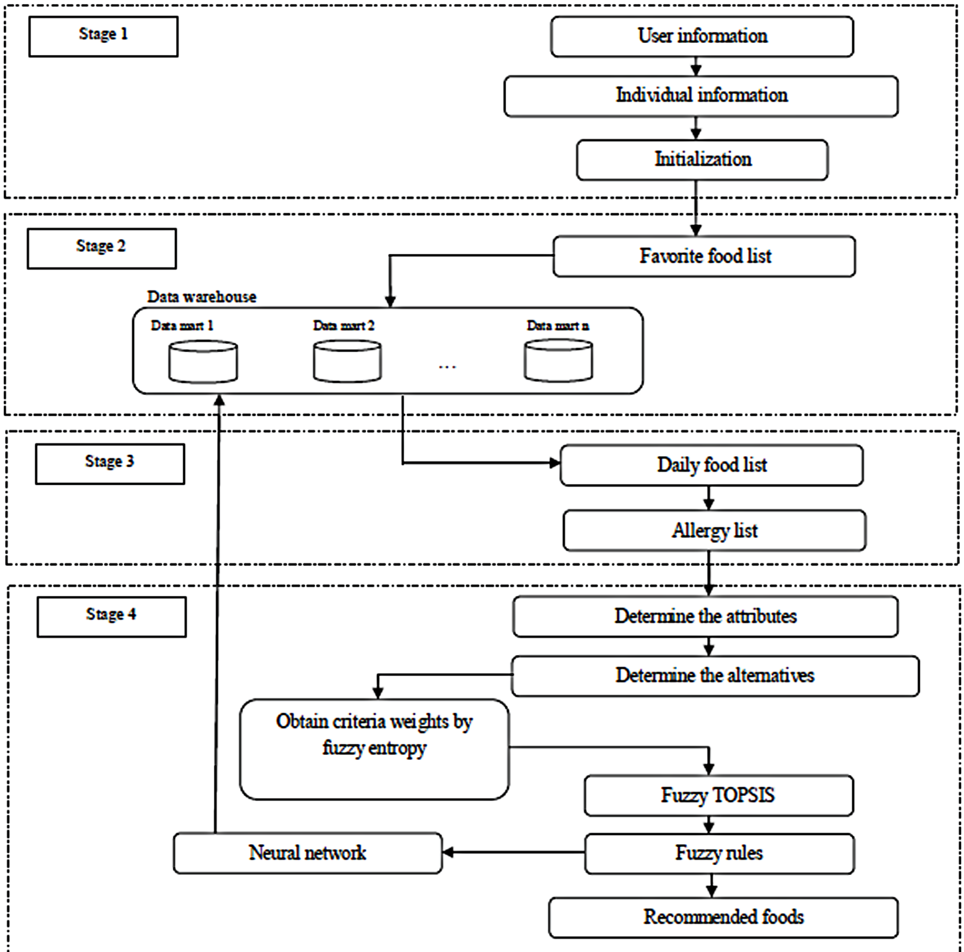


Figure 5. Decision information module

Figure 6. Favorite food module

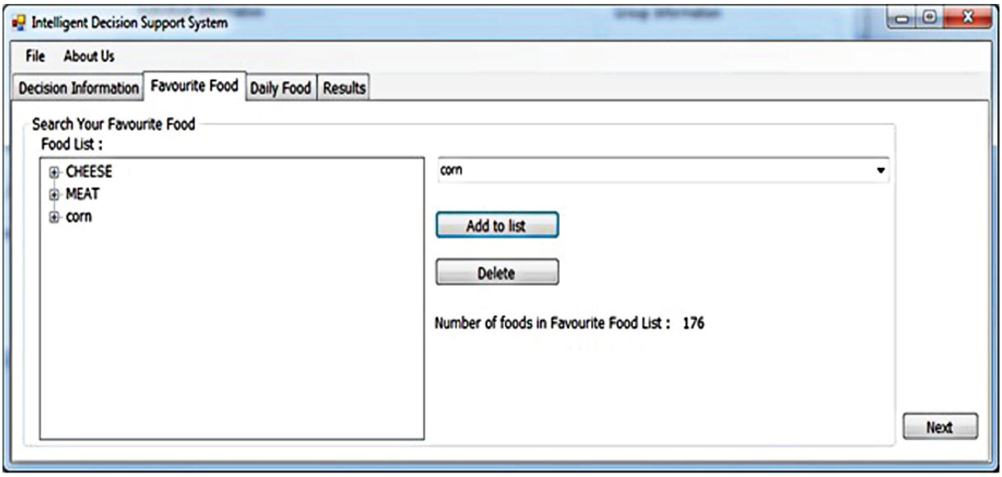
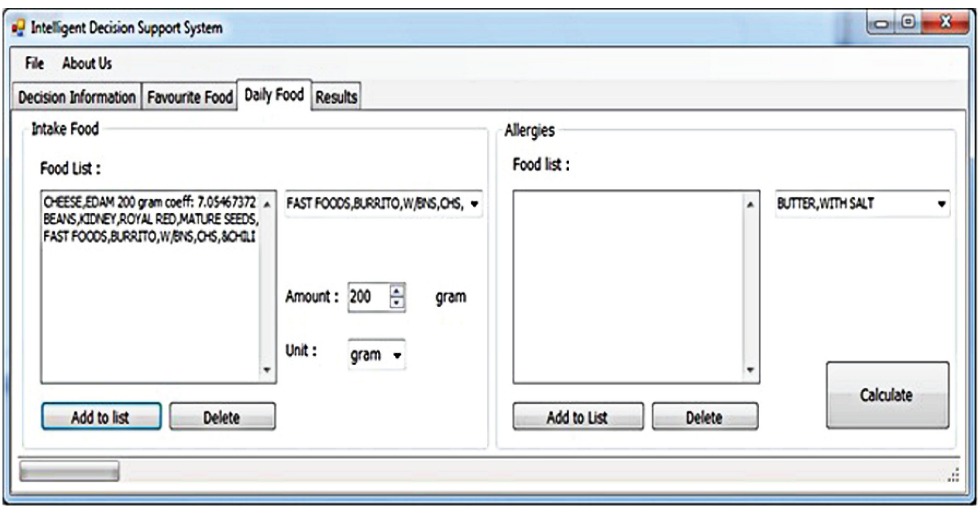
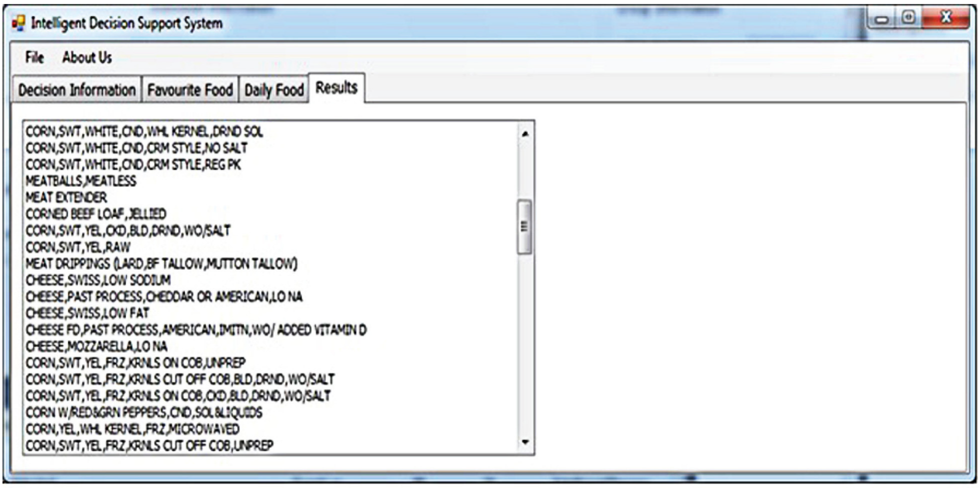


Figure 7. Daily food module



for the body's survival. Any person should be aware of energy status in order to keep the balance of energy and make an optimized decision regarding nutrition consumption. This study is a termination of a combination view to healthcare and decision making concepts. TOPSIS is widely applied in multi criteria decision making contexts. We have applied the TOPSIS method to optimize nutrition therapy problem and an implement a decision support system which has reduced technological barriers and made it easier and less costly to provide decision-relevant information. Also in this model-driven DSS we have considered uncertainty and fuzziness to approach the computation and results to reality. An IDSS is developed through a set of fuzzy

Figure 8. Result module



rules to implement the nutrition therapy problem and to extract knowledge about energy control and its effects on body status in the long term. In addition, ANN provides an adequate feasibility to disclose latent knowledge. The application of this expert system is comfortable and flexible for any person in different ages and conditions and can help to implement a successful nutrition plan which includes the assessment for entire nutrients and key elements specially energy.

Future work will focus on: (a) incorporating an additional set of fuzzy rules that will create a web-based expert system for medical nutrition therapy, (b) analyzing the effects of the parameters involved in the learning mechanism, (c) investigating effects of turning rule bases by increasing the number of fuzzy values of the linguistic variables involved, e.g., from three (low, medium, high) to five (very low, low, medium, high, very high).

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ENDNOTES

1 proteins, fats, and carbohydrates
2 vitamins and minerals

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