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Prevention of Obesity using Artificial Intelligence Techniques

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Abstract- Obesity has many causes. The reasons for the imbalance between calorie intake and consumption vary by individual. Age, Sex, Genes (GAD2), Negative Emotions, Diseases and Drugs, and environmental factors (Energy imbalance, Larger Portion sizes, High-calorie foods,) all may contribute. The most important environmental factor is lifestyle. Eating habits and activity level (Lack of physical activity) are partly learned from the people. Pregnancy: Women tend to weigh an average of 4-6 pounds more after a pregnancy than they did before. All these factors are characterized by uncertainty, vagueness and inaccuracy. In this work, we found it useful to use techniques of artificial intelligence in their treatment especially fuzzy logic inference. The use of the fuzzy logic model, demonstrate his capability for addressing problems of uncertainty and vagueness in data. The fuzzy model was structured to prevent apparition of obesity according the conditions in inputs of system (9 factors). After the system is completely constructed, it can learn new information in both numerical and linguistic forms. Each parameter involved with a degree in membership function, a data base of the rules is established, the result to the output of the program is the degree of occurrence of moderate, severe or pathogenic obesity.

Keywords-*Obesity; Artificial Intelligence.*

I. INTRODUCTION

To make medical decisions, physicians often rely on conventional wisdom and personal experience to arrive at subjective assessments and judgments. Recently there has been heightened concern over the burden of unwanted variation in clinical practice [23;1]. As a result, physicians are increasingly being asked to adhere to explicit guidelines that have been agreed on by the medical community at large [8]. Such guidelines often have a logical structure that makes them suitable for computer implementation. For many situations, however, the variable nature of disease and patient characteristics makes it difficult, even impossible, to decide exactly what should be done in every conceivable set of circumstances. In such situations, the physician must depend on intuitive decision making, sometimes described as the art of medicine [16]. In this study, we explore the causes of obesity that defined by an excess of body fat. The excess weight may come from muscle, bone, fat, and/or body water. The presence of excess fat in the trunk or abdomen out of proportion to total body fat is an independent predictor of risk factors and morbidity [9;10;11;20]. Obesity is associated with many serious preventable diseases including heart disease, diabetes, high blood pressure, stroke, gallbladder disease, osteoarthritis, and respiratory disorders. The increase of obesity in children and adolescents has become a major public health concern worldwide [15]. The prevalence of obesity varies in different populations and further variations depend on age and sex. [3;19;22] In the United States, recent reports show that 1 in 5 adult Americans are obese [2] in Saudi adults and, like the developed countries of the world, obesity may be regarded as an epidemic in Saudi Arabia [25]. There are a number of etiological factors producing obesity and these include both genetic, endocrine alterations and environmental factors and hence it is classified as a multifactor disorder [12]. In addition, the distinct and changing economic, social, cultural, and environmental factors play a significant role in the onset of obesity [20]. All causes of obesity are characterized by their imprecision and their uncertainty. A predictive model is created and extensive data collection has been done. However, significant differences between predicted model using artificial intelligence system and other numerical models is the analysis of real data in a fuzzy environment that fits perfectly with the case under consideration. In this paper, we present a software tool able to store in a database all relevant information expressed on one hand as qualitative or quantitative data and on the other hand as precise or imprecise data. To retrieve the more relevant information from the database, we use queries where criteria may be expressed as fuzzy values in order to enhance the flexibility of the search to compute, in addition to the nearest data, an estimation of searched values. The architecture of this software tool is structured as a category-based reasoning system.

II. FUZZY LOGIC INFERENCE

The fuzzy logic approaches, a sub-field of intelligent systems, are being widely used to solve a wide variety of problems in medical, biological and environmental applications. Fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. The above-mentioned capabilities make fuzzy logic a very powerful tool to solve many biological problems, where data may be complex or in an insufficient amount. The fuzzy logic concept provides a natural way of dealing with problems where the source of imprecision is an absence of sharply defined criteria rather than the presence of random variables. The fuzzy approach considers cases where linguistic uncertainties play some role in the control mechanism of the phenomena concerned [7]. Fuzzy inference systems (FIS) are powerful tools for the simulation of nonlinear behaviours with the help of fuzzy logic and linguistic fuzzy rules [14]. For medical expert systems, the theoretical framework of fuzzy logic provides a rich environment from which to choose. The adequacy of each approach is borne out by the success of the model in practice [17]. For example, there is not a straight-line relationship between the BMI and the degree of overweight. An individual with a BMI<25 is an individual not suffering from any kind of overweight (the degree of membership to the "overweight" set is 0). An individual with a BMI>30 is definitely overweight (the degree of membership to the "overweight" set is 1). For BMI values in between 25 and 30, the degree of membership would have fractional values between 0 and 1 [14]. This section briefly summarizes the basic concepts related to the analysis of the intensity of overweight in the framework of the fuzzy set theory.

In this study, we take to decision algorithms using the inference engine that makes inferences on a fuzzy rule system. For all the algorithms presented below there is a common rule form for rules that associate an observation vector.

$a= (a^{(1)}, a^{(2)}{}_{, \dots} a^{(n)})$

with a diagnosis. Further, we assume the following general form of the k-th rule in the system (k = 1, 2, …K):

If $a^{(1)}$ *is* A_{1k} *AND …AND* $a^{(n)}$ *is* $A_{n,k}$ *THAN b is* B_k

where A_{ik}, are fuzzy sets (whose membership functions are designated by ($\mu_{Ai,k}$) that correspond to the nature of particular observations (for simplicity we assume the sets to be triangular fuzzy numbers) whereas k B is a discrete fuzzy set defined on the diagnosis set, with the k B m membership function. The particular decision algorithms to be used in obesity prevention have in common both the inference engine and the procedure for rule system derivation from the learning set. In the proto-formal deduction rule, the syllogism:

Q_1 A's are B's **AND** Q_2(A&B)'s are C's **THAN** Q_1Q_2A's are (B&C)'s.

Example, Overeating causes obesity (precision) most of those who overeat become obese. Overeating and obesity causes high blood pressure (precision) most of those who overeat and are obese have high blood pressure. We overeat and are obese; the probability that we will develop high blood pressure is most [23].

III. FUZZY LOGIC MODELLING

A great clinical interest exists for evaluating overweight and obese patients to determine the risks inherent with these conditions, to prescribe and control conservative treatments, and to indicate when surgical treatment is needed. In the last 30 years, only the overweight and obesity rating system, which uses the body mass index (BMI), has been internationally recognized [12] (Table 1).

Table 1. Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults.

Classification	*BMI*
Overweight	25 to 29.9
Obesity Class I	30 to 34.9
Obesity Class II	35 to 39.9
Morbid Obesity Class III	≥40

In traditional set theory, something either belongs to a set or does not depending on whether it fits the definition for that set. In fuzzy set theory, something can partially belong to a set. For example, let us assume, that the variable Body Mass Index 'BMI' has rang of values where overweight is considered to be between 25 to 29.9, whereas low is below this rang, and obese above this rang. In traditional set theory, a value of BMI of 29 would be classified as an overweight, whereas 30 would be obese (Fig. 1). With fuzzy sets, a value for a variable can partially belong to asset and have a degree of membership function anywhere between zero and one (i.e. $0 \le \mu \le 1$) (Fig.2). Relationships among fuzzy sets are expressed as a series of 'if-then' rules to form a rule base. One of the most widely known fuzzy logic modelling is a general description of the basic steps in the process, using an obesity modelling. [4]. the number of fuzzy sets created determines the number of rules in the 'if-than' rule base. One rule is used for each fuzzy set of output.

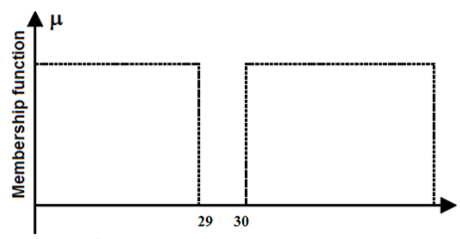

Fig. 1 : A value for a variable to a set or does not belong to a set

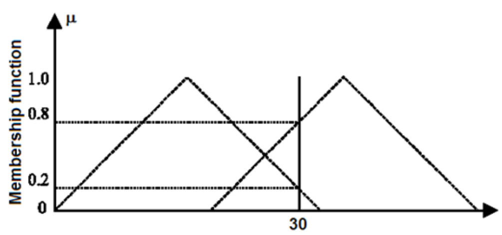

Fig. 2 : A value for a variable can partially belong to a set and have a degree of membership anywhere

Basically, any fuzzy logical model constitutes three parts: the fuzzy membership function, fuzzy decision, and fuzzy reasoning [6]. In this study, ten inputs are chooses (X_1 ; X_2 ;…X_{10}) as mentioned before. The output of the fuzzy logic model is Y. By using fuzzy sets, we can formulate fuzzy if-then rules, which commonly used in our daily expression. We can use a collection of fussy rules to describe a fuzzy system's behaviour this forms the fuzzy inference systems. We are going to use fuzzy inference system exclusively, where the output equation of each rule is a linear equation. First, we find the membership grades of the IF parts of the rules; the heights of the dashed line represent these values. Since the pre-conditions in the IF part are connected by AND, so we use multiplication to find the firing strength of each rule. Both the different levels of input and output are defined by specific membership function for the fuzzy sets. The model has a multivariable system with N input and one output variable.

Assemble input-output dataset:

As the effect of each parameter remains in the field of imprecise and fuzzy, each variable is represented by a membership function. The degree of influence on the occurrence of obesity is reflected by a degree in the fuzzy membership function. The first step is to collect all inputs variables (e.g., The Sex, Age, Gene GAD2, High-calorie foods, Fast food infiltration in our culture, Lack of physical activity, Sociology of Food, Energy imbalance, Larger Portion sizes, Diseases and Drugs, Negative Emotions, Early menarche) and the consequence as output (e.g. the value of BMI).

IV. FUZZIFICATION OF INPUTS

The data for the inputs were classified into three linguistic categories: The input –Age- [young, adult, old]. In the same way, all other inputs are fuzzyfied. A value is assigned to each variable (the genetic influence, the height calorie foods, the culture foods, the food quality, the physical activity, the energy imbalance, the diseases and drugs, the negative emotions, the early menarche) are represented by values from [0 – 4]. The sexes of person are defined by one or two (Fig. 3.a, b).

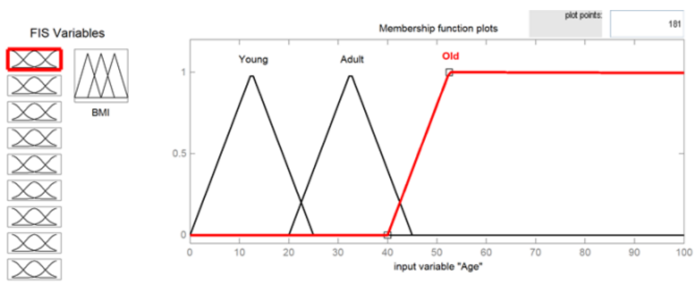

Fig. 3.a: The discourse universe of input (Age) Is classified in three linguistic categories: Young, Adult, Old

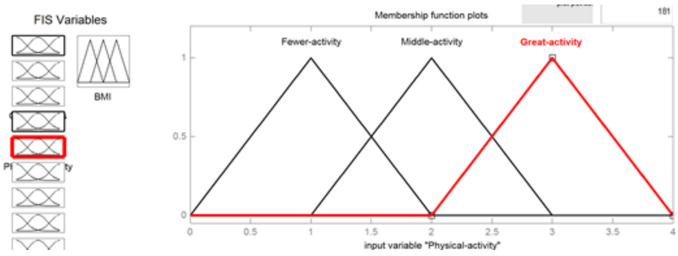

Fig. 3. b. The discourse universe of input (Physical activity) is classified in three linguistic categories: Fewer activity, Middle activity, and Great activity.

V. FUZZIFICATION OF OUTPUT

The data for the output (the BMI value) was classified into three linguistic categories: BMI 25 to 45 (overweight); (moderately obese); or (extremely obese) (Fig. 4).

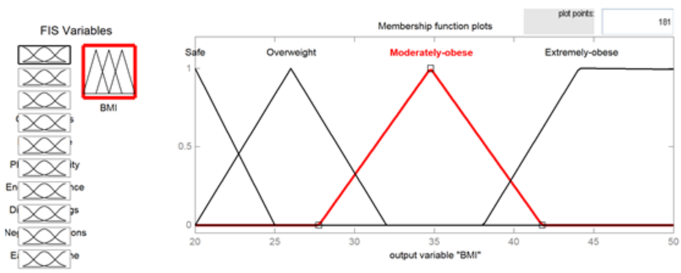

Fig. 4. The discourse universe of output (BMI) is classified in three linguistic categories: overweight, moderately obese, extremely obese.

VI. FUZZY RULES

The rules determined by the choice of the fuzzy membership function are defined for each input variable. In general form, each fuzzy rule is written as were A1 and A2 are the fuzzy sets that describe the nature of the inputs, such as young, adult, or old. The linguistic control rules of this system are given by [18]:

If X_1 IS $X_1(1)$ **and** X_2 IS $X_2(2)$ **and**…Xn IS Xn(n) **than** Y_1 is $Y_1(1)$

VII. DEFUZZIFIER

This system has one output that describes the function of human, in fact explains the contribution of each factor on obesity apparition. We can say that it shows the probability of normal function and disease. The crisp value output is given by the defuzzyfication process after estimating its input value. In this system we have center of average (C.O.A) method which has the mathematical expression that is.

$$(\sum Si.\,Ri)\;/\;(\sum Ri)$$

In the defuzzyfication the exact expression is obtained with "centroid" method according to validity degree. The output value according to the inputs values obtained from the designed fuzzy engine system.

Example :

If Age **is** Young, **and** Genetic influence **is** no, and quality middle **is** poor quality, **and** food culture **is** fewer exposed, **and** physical activity **is** middle activity, **and** energy imbalance **is** consumed>used, **and** diseases-drugs **is** not affected, **and** negative emotions **is** moderately affected, **and** sex **is** female, **and** menarche **is** early maturity, **than** the BMI **is** overweight…

VIII. RESULTS AND DISCUSSION

The factors effect on obesity system is based on fuzzy logic model. It is designed for measurement of different parameters. This system consists of ten inputs variables. The rule base of this system is used to determine the output parameter value: (overweight); (moderately obese); or (extremely obese, according to the ten inputs values. Ten fuzzyfiers and one defuzzyfier are used in this system. MATLAB-simulation is used by applying rules. Fig. 5 shows the MATLAB- rule viewer and simulation result.

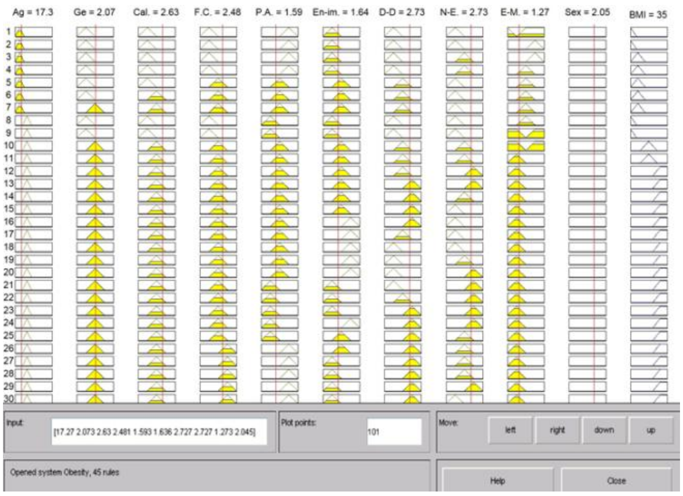

Fig. 5. Application Example: attribution random variable inputs and direct reading of the output variable

One of the problems in obesity causes modeling is the vagueness in the values of agents, arising either form natural randomness in physiological and bodies. In this study, we used different parameters. The data were analyzed by the fuzzy logic modeling technique in an attempt to predict level of obesity. With the fuzzy modeling, we can represent imprecise data and produce a precise output in the form of fuzzy members. From the results obtained by this study, appear to be a useful tool for future overweight effect-testing on different factors risk identification, quantification and development of early warning systems. The designed system can be extended for any number of inputs. As the ten considerate inputs, similarly we can define these system more than ten inputs to get more efficient result.

The fuzzy logic inference system shows that the output ‘BMI’ corresponding to any input factor causes of obesity. As all causes of obesity are characterized by their complexity and uncertainty, fuzzy logic as a tool for analysing such data is perfectly adequate. However, other parameters that are not taken into consideration in this study may be included. The model is extendable for greater precision in the analysis. The proposed system provides an analytical result based on the contribution of each input parameters depending on its degree of membership function. As the basis of rules covers all possibilities, the result reflected faithfully the physical reality of the patient.

IX. CONCLUSION

The artificial intelligent system using fuzzy logic method could extend our understanding of causes of obesity, and the intelligent software created in this study could be used for prevention of obese patients and as a part of a therapy potentially improve quality of life and decrease the morbidity and mortality associated with obesity. The goal of this study is to design and perform a pilot investigation which will provide preliminary data. Modern methods of computational intelligence such as fuzzy logic are used to achieve the highest accuracy of pattern recognition. The fuzzy logic inference system shows that the output ‘BMI’ corresponding to any input factor causes of obesity. The result of the fuzzy program so far, is a numeric and symbolic terms of body mass index, using the fuzzy inputs data in the universe of discourse (overweight, moderately obese or extremely obese). As the input parameters are characterized by uncertainty, we believe that this tool is very adequate. We emphasize that our fuzzy system is not meant to replace or substitute for an experienced physicians; on the contrary, we envisage that the fuzzy logic system should be viewed as a decision support in the most accurate

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