# Design Methodology of Fuzzy Expert System for the Diagnosis and Control of Obesity

Uduak Umoh
Department of Computer Science, University of Uyo, Uyo, AKS, Nigeria

Etebong Isong
Department of Computer Science, Akwa Ibom State University, Mkpat Enin, AKS, Nigeria

**Abstract**

Both developed and developing nations of the world have overtime experienced enormous increase in food and other consumables production. This has led to a rise in calorie intake by people living in these nations of the world. As calorie intake increases in the human system, lack of early detection or control leads to obesity. The study of obesity is gaining utmost importance because of the major health issues associated with it. If an obese prone patient is detected early enough, then quite a number of diseases can be prevented. The ability of fuzzy logic to reason with uncertain and imprecise data in addressing the specific problem of diagnosis and monitoring of diseases in our society cannot be over emphasized. In this paper we design methodology of fuzzy expert system to diagnose and monitor obesity in persons at early stage. The study will help reduce to a great minimum the fast rise of obesity in our society and the world at large. The proposed study is validated with MatLab, and is used as a tracking system with accuracy and robustness.

**Keywords**: Obesity, Fuzzy Inference System, Body Mass Index, Body fat, Waist circumference.

## 1. Introduction

Both developed and developing nations of the world have overtime experienced enormous increase in food and other consumables production. This has led to a rise in calorie intake by people living in these nations of the world. As calorie intake increases in the human system, lack of early detection or control leads to obesity. The foods we eat every day contribute to our well-being. Foods provide us with the nutrients we need for healthy bodies and the calories we need for energy. If we take in more calories than we burn, the extra food turns to fat and is stored in our bodies. If we overeat regularly, we gain weight, and if we continue to gain weight, we may become obese. To reduce these risks, much attention is being paid to methods of weight loss in Nigeria, and there is increasing awareness of the need to monitor caloric and nutrient intake, as well as an emphasis on the healthiness and balanced nature of food intake

Obesity results from the accumulation of excess fat on the body. It has many serious long-term consequences to health, and it is a leading cause of preventable deaths in the world. Obesity is defined as having a body mass index (BMI) of greater than 30. The BMI is a measure of your weight relative to ones' height. BMI is a mechanism to measure weight excess extensively used in a myriad of epidemiologic studies, and is incorporated with clinical practice because of its simplicity. However, it does not properly evaluate the body fat (BF) proportion because it fails to distinguish lean muscle mass from body fat. The BF measurement has more value than global body mass measurements since the harmful factor in obesity is the accumulation of fat in the body, and lean muscle mass. More than two-thirds of Americans are overweight, including at least one in five children. Obesity is on the rise in our society because food is abundant and most of us are employed in positions that require little to no physical activity. On the bright side, recent data suggest that childhood obesity, while still high, may no longer be on the rise (Eknoyan, 2008) (Okorodudu, 2010).

The study of obesity is gaining utmost importance because of the major health issues associated with it. A lot of sicknesses arise due to obesity, such as diabetes, high blood pressure, cholesterol, stroke etc. If an obese prone patient is detected early enough, then quite a number of diseases can be prevented. The use of the body mass index calculator has done quite a job but it does not guarantee the complete detection of obesity as other factors such as genetic line are not considered in the body mass calculator (Adams et al. 2007) .

The major problem in diagnosing and predicting a disease is the uncertain variations in risk factors which occur due to the sedentary life style, food habit, stress, age, environment etc. Generally the risk factors in medical domain are classified as controllable (Blood Pressure, Lipids, Obesity, Hyperglycemia), non-controllable (age, heredity, sex) and contributing factors (smoking, alcohol, stress). Due to uncertainty, **i**nformation is incomplete, fragmentary, not fully reliable, vague, contradictory, or deficient in some way. The existence of uncertain factors with errors is numerous in medical domain and it is to be solved in an efficient way.

The medical errors can be solved with the help of experts' knowledge. As the experts' knowledge are so valuable and tacit in nature which cannot be used as it is, therefore interpreting them in terms of rules is the best approach to resolve the uncertainty. Hence, this paper proposes design a FKBS to overcome the uncertainties and to predict the risk of obesity. This will help to control the controllable risk factors for proper diagnosis and control of obesity. The flaws mentioned above prompt the design of a fuzzy logic expert system that is capable of diagnosing obesity in persons at an early stage. The greatest advantage of using fuzzy logic lies in the fact that scientists can model non-linear, imprecise, complex systems by implementing human experience, knowledge and practice as a set of inference (or fuzzy) rules that use linguistic (or fuzzy) variables. Intervention of the development could help reduce to a great minimum the fast rise of obesity in developed and developing nations.

The objective of paper is to (i) develop a fuzzy expert system to detect obesity using body mass index calculator, body fat and waist circumference. (ii) design a database model to hold information about decision variable for the diagnosis of obesity. (iii) design a fuzzy logic model for the diagnosis of obesity. In order to accomplish our objectives, we adopt the following methodology: (i) Review and study of relevant literatures on fuzzy logic, disease monitoring and diagnosis, healthcare system and obesity. (ii) Study and understand the characteristics of existing systems as well as gathering of data through medical experts/consultants. (iii) We explore system analysis and design tool in the analysis of the project. (iv) Object oriented design tool is employed in the design of our system. (v) The study employs Fuzzy logic toolbox in Matlab Simulink for simulation and evaluation of results operating on window 7 platform. The results of investigation shows better performance in reducing the fast rising epidemic of obesity in our society using very simple task and also make easy the tasks of patients undergoing various medical tests, which most of them consider risky, tedious and time consuming.

## 2. Literature Review

According to Miyahira et al. (2011), the search for a more accurate method to evaluate obesity and to indicate a better treatment is important in the world health context. Body mass index (BMI) is considered the main criteria for obesity treatment and BSI. Nevertheless, the fat excess related to the percentage of Body Fat (%BF) is actually the principal harmful factor in obesity disease that is usually neglected. The study proposes a fuzzy model to validate a previous fuzzy mechanism by associating BMI with %BF that yields the Miyahira-Araujo Fuzzy Obesity Index (MAFOI) for obesity evaluation, classification, analysis, treatment, as well for better indication of surgical treatment.

In Rama and Nagaveni, (2010), fuzzy knowledgebase system (FKBS) is designed to perform the optimum control on high risk controllable risk factors to predict the risk of diabetic nephropathy in terms of Glomeruler Filtration Rate (GFR), by acquiring and interpreting the medical experts' knowledge. The FKBS captures the existence of uncertainty in the risk factors of Diabetic Nephropathy, resolves the renal failure with optimum result and protects the patients from End Stage Renal Disorder (ESRD). In Arunraj, (2012), a model is proposed for the control of hypertrophic obesity and hyperplastic obesity, using fuzzy mathematical modeling. The study applies Fourier's law to express the equation of obesity, which is known as diffusion equation. The effects of treatment process over the obesity and the natural process of obesity with no treatment are determined with the use of fuzzy rule based system. The result indicates that the control of the obesity depends on both the degree of obesity with its induction level and on appropriate treatment levels.

In Margaret et al. (2013), an attempt is made in this paper to design and develop such diagnosis system, using a rough set. The system developed is evaluated using a simple set of symptoms that is added to clinical data in determining diabetes and its severity. In Poorna and Subith, (2015), Fuzzy inference is employed to develop a computer program that can automatically find out the certainty whether a patient having some specified symptoms suffers from any one of a set of suspected diseases. This certainty is specified as a crisp percentage value for every suspected disease. In Manju Khannaet al. (2015), a study of obesity in children using fuzzy logic is carried out. The study includes the Body Mass Index and physical activity which are taken into account for the analysis of obesity in children.

 

In Nnomako et al. (2011), a fuzzy expert system framework that combines case-based and rule-based reasoning effectively to produce a usable tool for Type 2 Diabetes Mellitus (T2DM) management is proposed. The major targets are on combined therapies (i.e., lifestyle and pharmacologic), and the recognition of management data dynamics (trends) during reasoning. The Knowledge base (KB) is constructed using fuzzified input values which are subsequently de-fuzziffied after reasoning, to produce crisp outputs to patients in the form of low-risk advice. The extended framework features a combined reasoning approach for simplified output in the form of decision support for clinicians. Ritha and Merline (2012), study contributing factors of childhood obesity like genetic, environmental, behavioral, metabolic, biochemical and social factors and its relationship. The paper investigates the most contributing / impactful factor of childhood obesity using Induced Fuzzy Cognitive Maps. In Ayilvaganan and Rajeswari, (2013), analysis study of fuzzy logic using blood pressure readings is investigated. In the paper, blood pressure values are taken as an input and applied using fuzzy algorithm and the output values are analyzed.

Cinetha and Maheswari, (2014), design a decision support System for Precluding Coronary Heart Disease (CHD) risk of patient for the next ten-years for prevention. The study identifies the major risk factors of Coronary Heart Disease (CHD) categorizing the risk factors in an order which causes high damages such as high blood cholesterol, diabetes, smoking, poor diet, obesity, hyper tension, stress, etc. Data mining functionalities are used to identify the level of risk factors to help the patients in taking precautionary actions to stretch their life span. Mukhopadhyay and Ghosh, (2011), study Fuzzy Logic and Dispositions for Medical Diagnosis. In this study, an attempt is made to show how fuzzy logic and its extension, particularly dispositions, can be used for modeling a medical diagnosis system. Shora et al. (2012), present a fuzzy decision making in case of a medical diagnostic system and compare the results with those of the Intuitionistic fuzzy decision making technique in a knowledge based decision support. In the study, both fuzzy and Intuitionistic fuzzy techniques are used to determine the cause of obesity.

Tong, et al. (2015) present an advancement of Automatic Anatomy Recognition, AAR to handle organs which are modified or resected by surgical intervention. The proposed method consists of an AAR step followed by support vector machine techniques to detect the presence/absence of organs. The AAR step employs a hierarchical organization of the organs for model building. For each organ, a fuzzy model over a population is built. The model of the body region is then described in terms of the fuzzy models and a host of other descriptors which include parent to offspring relationship estimated over the population. Experimental results show that AAR techniques can be combined with machine learning strategies within the AAR recognition framework for good performance in recognizing missing organs, in our case missing tonsils in post-tonsillectomy images as well as in simulating tonsillectomy images. Chin et al. (2013) explores fuzzy inference method to develop a personal diet and caloric intake monitoring system for use on smart phones.

## 3. Research Methodology

### *3.1 System Architecture*

The conceptual architecture of our model is based on (Umoh et al. 2011) and presents in Figure 1. The conceptual architecture consists of knowledge engine, knowledge base which is made up of database model and fuzzy logic model and user interface. Figure 2 presents the database model for obesity diagnosis. FESDMO Object Mode is shown in Figure 3. Figure 4 presents FESDMO Fuzzy Logic Model.

PATIENT BIO DATA [ The p_no collects Patient's identification number, p_surname collects the Patient's surname, p_othernames collect Patient's first name, p_gender collects Patient's sex, p_dateofbirth Patient's date of birth, p_phoneno collects Patient's telephone number, p_email collects Patient's email address, p_address collects Patient's contact address, p_occupation collects Patient's occupation, p_religion collects Patient's religion, p_nextofkin collects the name of the of the patients next of kin] EXPERT [ doc_id collects the medical expert identification code, doc_name houses the medical expert's name] LOGIN [password, doc_Id, serial number] REPORT [doc_Id, p_no, p_surname, p_othernames, p_gender, Obesity, Degree, Recommendation, and Prescription]

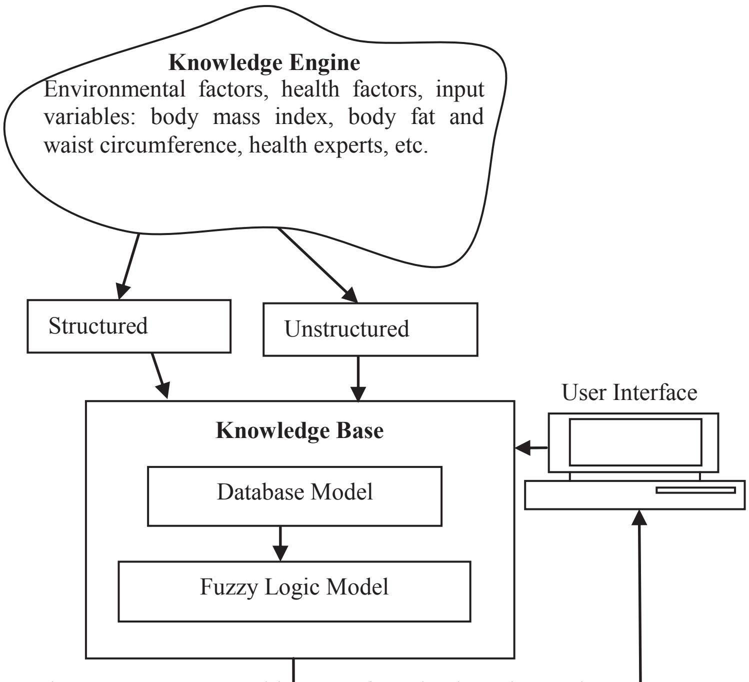


Figure 1: System Architecture for Obesity Diagnosis System

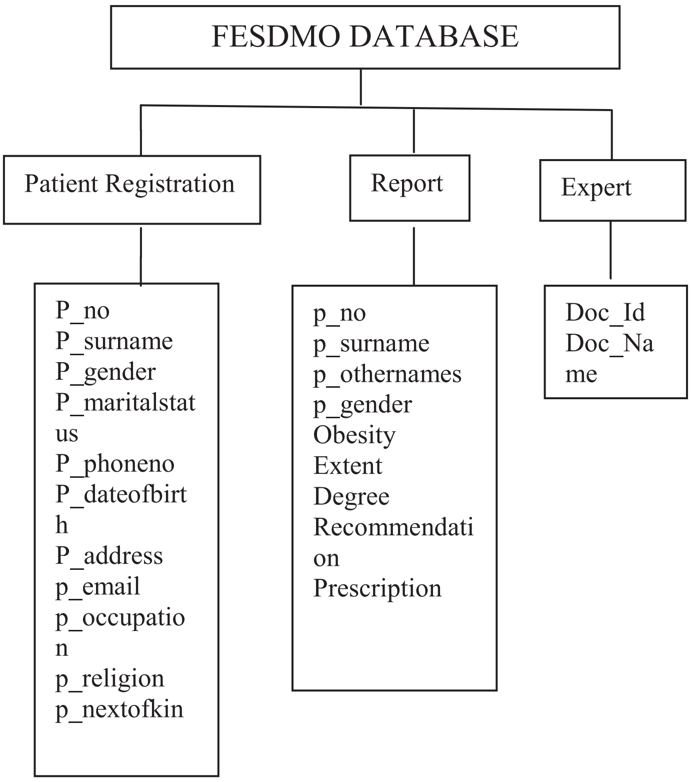


Figure 2: Database Model for diagnosis of obesity

$$\mu(x) = \begin{cases} 0 & \text{if } x < a_1 \\ x - a_1/a_2 - a_1 & \text{if } a_1 < x <= a_2 \\ a_3 - x/\ a_3 - a_2 & \text{if } a_2 < x <= a_3 \\ 0 & \text{if } x > = a_3 \end{cases}$$

]

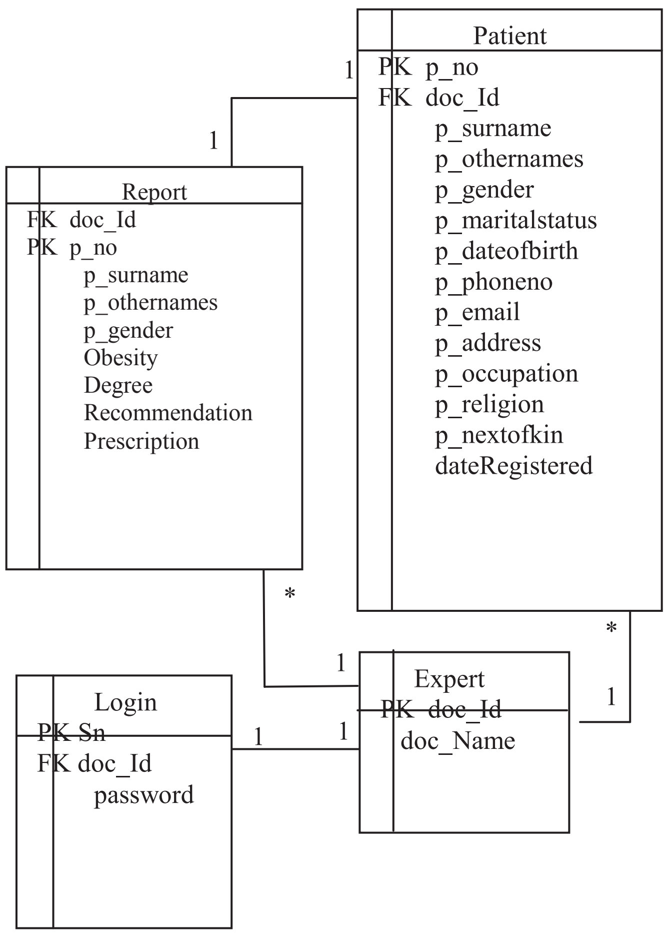


Figure. 3: FESDMO Object Model

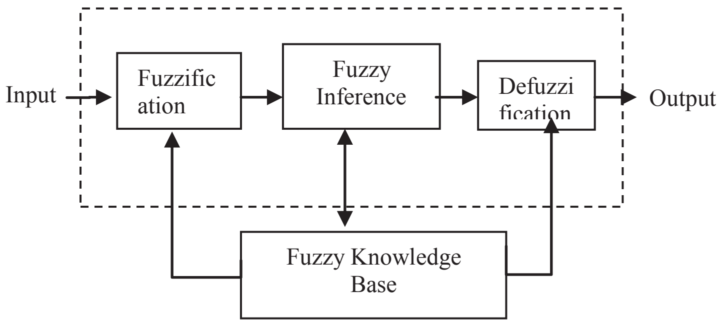


Figure 4: FESDMO Fuzzy Logic Model

 

The main building units of a fuzzy logic design of an obesity diagnostic system involve the following:

a. Fuzzification Unit: This unit converts the crisp input into membership value.
b. Fuzzy Inference Unit: uses the rules in the rule base to compare the input gotten from the fuzzification unit with factual knowledge in the database.
c. Fuzzy Knowledge Base Unit: Hold rules and data used by the inference engine.
d. Defuzzification Unit: This unit converts the membership value to the crisp output.

The fuzzy linguistics is defined on both input and output parameter as follows: Body Mass Index: {low, moderate, high}, Body Fat: {low, normal, high}, Waist Circumference: {small, medium, large} and Obesity: {healthy, overweight, obese}. The input parameters are in the range, $15kg/m^2 – 35kg/m^2$, 15% - 35% and 30cm – 120cm, for body mass index (BMI), body fat (BF) and waist circumference (WC) respectively. The linguistic expressions for both input and output linguistic variables for obesity and its corresponding membership functions are evaluated using triangular membership function. Triangular curves depend on three parameters $a_1$, $a_2$, and $a_3$ and are given by equation (1); $a_2$ defines the triangular peak location, while $a_1$ and $a_3$ define the triangular end points.

$$\mu(x) = \begin{cases} 0 & \text{if } x < a_1 \\ x - a_1/a_2 - a_1 & \text{if } a_1 < x <= a_2 \\ a_3 - x/\ a_3 - a_2 & \text{if } a_2 < x <= a_3 \\ 0 & \text{if } x >= a_3 \end{cases} \quad (1)$$

Fuzzy logic toolbox in MATLAB 7.5.0 is employed in this study for the membership function plots for the Body Mass Index (BMI), Body Fat (BF), Waist Circumference (WC) and Output (Obesity) and present in Figures 5-8 respectively. The degree of membership (DOM) is determined by plugging the selected input parameter (body mass index, body fat, waist circumference) into the horizontal axis and projecting vertically to the upper boundary of the membership function(s).

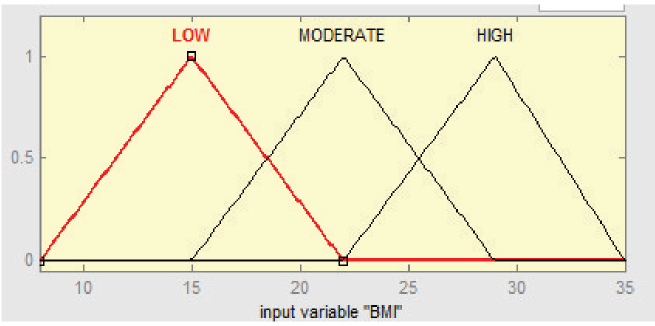


Figure 5: Membership Function for Body Mass Index (BMI)

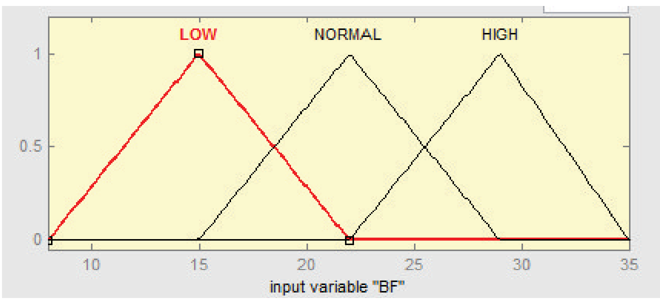


Figure 6: Membership Function for Body Fat (BF)

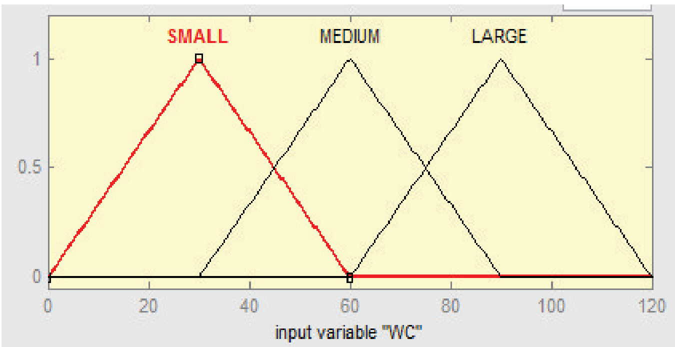


Figure 7: Membership Function for Waist Circumference (WC)

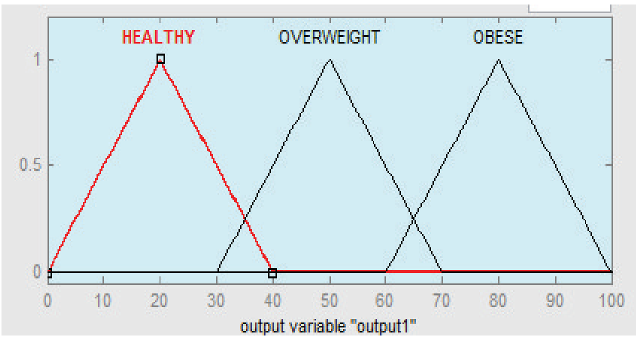


Figure 8: Membership Function for Output (Obesity level)

Membership Matrix Tables for body mass index (BMI), body fat (BF) and waist circumference (WC) are presented in Tables 1-3 respectively.

Table 1: Membership Matrix Table for BMI

| Linguistic Set | Quantized Level | | | |
|---|---|---|---|---|
| | 20 | 26 | 30 | 33 |
| LOW | 0.3 | .0. | 0 | 0 |
| MODERATE | 0.7 | 0.4 | 0.0 | 0.0 |
| HIGH | 0.0 | 0.6 | 0.9 | 0.35 |

Table 2: Membership Matrix Table for BF

| Linguistic Set | Quantized Level | | | |
|---|---|---|---|---|
| | 15 | 22 | 26 | 34 |
| LOW | 1.0 | 0.0 | 0.0 | 0.0 |
| NORMAL | 0.0 | 1.0 | 0.4 | 0.0 |
| HIGH | 0 | 0 | 0.53 | 0.2 |

Table 3: Membership Matrix Table for WC

| Linguistic Set | Quantized Level | | | |
|---|---|---|---|---|
| | 40 | 70 | 93 | 102 |
| SMALL | 0.53 | 0.0 | 0.0 | 0.0 |
| MEDIUM | 0.4 | 0.7 | 0.0 | 0.0 |
| LARGE | 0.0 | 0.3 | 0.97 | 0.5 |

From our knowledge base, 27 rules are defined for the rule base of obesity diagnosis system and presented in Figure 9:

RULE 1: IF BMI = LOW AND BF = LOW AND WC =SMALL THEN TIP = HEALTHY.
RULE 2: IF BMI = LOW AND BF = LOW AND WC = MEDIUM THEN TIP = HEALTHY.
RULE 3: IF BMI = LOW AND BF = LOW AND WC = LARGE THEN TIP =HEALTHY.
RULE 4: IF BMI = LOW AND BF = NORMAL AND WC = SMALL THEN TIP =HEALTHY
RULE 5: IF BMI =LOW AND BF = NORMAL AND WC = MEDIUM THEN TIP =OVERWEIGHT
RULE 6: IF BMI = LOW AND BF = NORMAL AND WC =LARGE THEN TIP =OBESE
RULE 7: IF BMI = LOW AND BF =HIGH AND WC = SMALL THEN TIP = HEALTHY
RULE 8: IF BMI =LOW AND BF =HIGH AND WC = MEDIUM THEN TIP =OVERWEIGHT
RULE 9: IF BMI= LOW AND BF = HIGH AND WC = LARGE THEN TIP = OBESE
RULE 10: IF BMI = MODERATE AND BF =LOW AND WC = SMALL THEN TIP = HEALTHY
RULE 11: IF BMI = MODERATE AND BF = LOW AND WC = MEDIUM THEN TIP = HEALTHY
RULE 12: IF BMI = MODERATE AND BF = LOW AND WC = LARGE THEN TIP = OBESE
RULE 13: IF BMI=MODERATE AND BF=NORMAL AND WC = SMALL THEN TIP = OVERWEIGHT
RULE 14 IF BMI = MODERATE AND BF = NORMAL AND WC = MEDIUM THEN TIP = OVERWEIGHT
RULE 15: IF BMI = MODERATE AND BF = NORMAL AND WC = LARGE THEN TIP = OBESE
RULE 16: IF BMI = MODERATE AND BF = HIGH AND WC = SMALL THEN TIP = OVERWEIGHT
RULE 17: IF BMI = MODERATE AND BF = HIGH AND WC = MEDIUM THEN TIP = OBESE
RULE 18: IF BMI = MODERATE AND BF = HIGH AND WC = LARGE THEN TIP = OBESE
RULE 19: IF BMI = HIGH AND BF = LOW AND WC = SMALL THEN TIP = HEALTHY
RULE 20: IF BMI = HIGH AND BF= LOW AND WC = MEDIUM THEN TIP = HEALTHY
RULE 21: IF BMI = HIGH AND BF = LOW AND WC = LARGE THEN TIP = OVERWEIGHT
RULE 22: IF BMI = HIGH AND BF = NORMAL AND WC = SMALL THEN TIP = OVERWEIGHT
RULE 23: IF BMI = HIGH AND BF = NORMAL AND WC = MEDIUM THEN TIP = OBESE
RULE 24: IF BMI = HIGH AND BF = NORMAL AND WC = LARGE THEN TIP = OBESE
RULE 25: IF BMI = HIGH AND BF = HIGH AND WC = SMALL THEN TIP = OVERWEIGHT
RULE 26: IF BMI = HIGH AND BF = HIGH AND WC = MEDIUM THEN TIP = OBESE
RULE 27: IF BMI = HIGH AND BF = HIGH AND WC = LARGE THEN TIP = OBESE

Figure 9: Fuzzy Rules of our Proposed System

The study adopts Mamdani MAX-MIN fuzzy inference method reason being that it gives precise results. In Mamdani MAX-MIN fuzzy inference method, the rules use the input membership values as weighting factors to determine their influence on the fuzzy output sets of the final output conclusion. In calculating the strength for each of the rule, the MIN above zero value of each of the variable in its AND functions is selected. The firing levels of the 27 rules are computed based on (Umoh et al, 2010) as shown in (2).

$$\rho_i = BMI_i(x_0) \wedge BF_i\,(y_0) \wedge WC_i\,(z_0),\ \ BMI_{i2}(x_0) \wedge BF_{i2}\,(y_0) \wedge WC_{i2}\,(z_0),\ ...\ \ BMI_{in}(x_0) \wedge BF_{in}\,(y_0) \wedge WC_{in}\,(z_0) \tag{2}$$

Where, $\rho_i$ is the matching degree of a given input which satisfies the condition of the ith rule and i = 1, 2,.., 27. The variable BMI represent body mass index, BF represent body fat and WC represent waist circumference. In this procedure, the degrees of truths (R) of the rules are determined for each rule by evaluating the nonzero minimum values using AND operator. Then $\alpha_i$ is assigned to the rule's consequence $C_i$ (w) as shown in (3).

$$C_i\,(w) = \alpha_i \tag{3}$$

The Mamdani max-min inference engine is evaluated to obtain the individual rule outputs as in (4).

$$C'_i(w) = (\alpha_{i1} \wedge C_{i1}(w)),\ (\alpha_{i2} \wedge C_{i2}(w)),\ \ldots(\alpha_{in} \wedge C_{in}(w)) \tag{4}$$

Where, $C_i\,'(w)$ is the individual rule's consequence.
The system output is computed by aggregating the individual rule outputs from all the rules using OR operator as presented in (50.

$$C(w) = C'_1(w) \vee C'_2(w) \vee C'_2(w) \vee \ldots \vee C'_n(w) \quad (5)$$

The paper adopts the weighted average of the elements in the support set defuzzification approach based on (Guney, 2009) and (Umoh, et al., 2011). Here each rule is weighted using it normalized weighting factor and the output of the fuzzy inference system is computed by the summation of all rule outputs as shown in (6).

$$\text{Crisp output, } Z = \sum_{k=1}^{27} \bar{\alpha}kZk = \left(\sum_{k=1}^{27} \alpha kZk\right) / \left(\sum_{k=1}^{27} \alpha k\right) \quad (6)$$

Where $\bar{\alpha}_i$ is a running point in a discrete universe, and $\sum \bar{\alpha}kZk$ is its membership value in the membership function.

## 4. Results and Discussion

This paper presents the design methodology of a fuzzy logic model for diagnosis and control of obesity based on Mamdani's direct approach. From the study, input and output linguistic variables are defined and assigned to both input and output variables. The study employs Triangular membership function where the variables in the system are manipulated and represented judiciously. The selection of membership functions and rule base determine the output. Rule base are defined based on the experience of system expert. We adopt Matlab®/Simulink® and its Fuzzy Logic tool box functions to develop a computer simulation showing the user interface and fuzzy inference to assist the experimental decision for the best control action. From the study, the crisp input values are converted to the fuzzy values by the input MFs. For example, the fuzzy inputs are selected at 26, 26 and 70 for BMI, BF and WC and their corresponding degree of membership evaluated and the result presented in Table 4. From Table 4, Rules 5, 8, 14, 6, 9, 15, 17 and 18 fire from the rule base presented in this work when body mass index (BMI), body fat (BF) and waist circumference (WC) are selected at 26, 26 and 70 and their corresponding degrees of membership are computed. We explore MAX_MIN inference to compute output membership function strengths from the possible rules.

The normalized weighting factor of each fired rule, $\bar{\alpha}k$, is computed for Overweight and Obese respectively based on (3). From (4), the output rule values are calculated for Overweight and Obese respectively. The crisp output is evaluated for these input conditions from (6). Table 5 shows rule base evaluation using the inputs 20, 15 and 40 for body mass index, body fat and waist circumference respectively. Table 6 shows rule base evaluation using the inputs 20, 15 and 40 for body mass index, body fat and waist circumference respectively.

Table 4 shows Rule base evaluation using the inputs 26, 26 and 70 for BMI, BF and WC

| Rule No. | Input Variable | | | Consequence | Non-Zero Minimum |
|---|---|---|---|---|---|
| | BMI | BF | WC | | |
| 5 | 0.30 | 0.40 | 0.70 | Overweight | 0.30 |
| 8 | 0.30 | 0.40 | 0.30 | Overweight | 0.30 |
| 14 | 0.30 | 0.53 | 0.70 | Overweight | 0.40 |
| 6 | 0.30 | 0.53 | 0.30 | Obese | 0.30 |
| 9 | 0.70 | 0.04 | 0.70 | Obese | 0.30 |
| 15 | 0.70 | 0.04 | 0.30 | Obese | 0.30 |
| 17 | 0.70 | 0.53 | 0.70 | Obese | 0.53 |
| 18 | 0.70 | 0.53 | 0.30 | Obese | 0.30 |

Table 5: Rule base evaluation using the inputs 20, 15 and 40 BMI, BF and WC

| Rule No. | Input Variables | | | Consequence | Non-Zero Minimum |
|---|---|---|---|---|---|
| | BMI | BF | WC | | |
| 5 | 0.26 | 1.0 | 0.70 | Healthy | 0.26 |
| 8 | 0.26 | 1.0 | 0.29 | Healthy | 0.26 |
| 14 | 0.60 | 1.0 | 0.70 | Healthy | 0.60 |
| 6 | 0.60 | 1.0 | 0.29 | Healthy | 0.29 |

Table 6: Rule base evaluation using the inputs 20, 15 and 40 for BMI, BF and WC

| Rule No. | Input Variables | | | Consequence | Non-Zero Minimum |
|---|---|---|---|---|---|
| | BMI | BF | WC | | |
| 26 | 0.26 | 1.0 | 0.70 | Healthy | 0.26 |
| 26 | 0.26 | 1.0 | 0.29 | Healthy | 0.26 |

Computer Engineering and Intelligent Systems
ISSN 2222-1719 (Paper) ISSN 2222-2863 (Online)
Vol.6, No.9, 2015


Using, Matlab Fuzzy Logic Toolbox, we insert the values of BMI, BF and WC as indicated in Tables 4 - 6 into the rule base under the view rule editor and the outputs are computed. The results of the rule base evaluation under view rule editor are presented in Figures 10 – 12 respectively. The input conditions in Figure 10 indicate that the patient has 67% overweight level of obesity risk in the body system. Therefore overweight level of obesity is expected with 67% possibility and required system response. It shows that the patient here is at 67% level overweight, indicating 67% (high) level risk of getting obese. With this result, the patient is advised by the doctor to check his/her diet and be involved in active physical exercise. The input conditions in Figure 11 indicate that the patient has 20% Healthy level in the body system. Therefore healthy level is expected with 20% possibility and required system response. The input conditions in Figure 12 indicate that the patient has 80% Obese level of obesity risk in the body system. Therefore obese level of obesity risk is expected with 80% possibility and required system response. This result shows that immediate medical advice and treatment is need for the patient as he/she is already obese with 80% level of influence.

From Figure 8, if we considering the degree of relationship between linguistic label and value of fuzzy output membership function, say "Healthy", when its value is 1.0, it indicates 100% possibility that the person healthy. This shows the totality that the person is healthy with a normal weight with zero level of overweight and obesity.

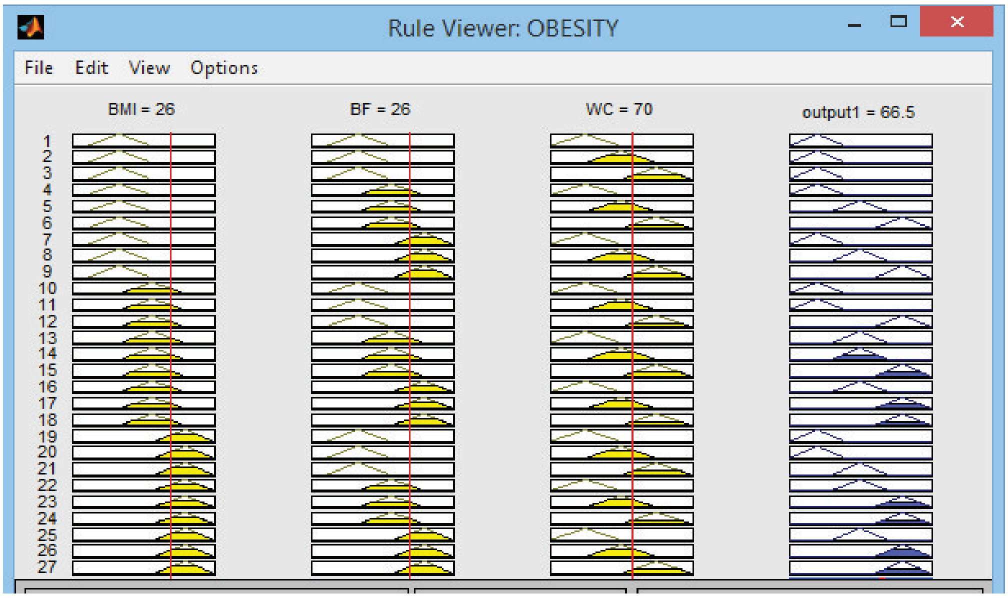


Figure 10: Graphical Construction of the Inference Mechanism of Fuzzy Sets in Table 4

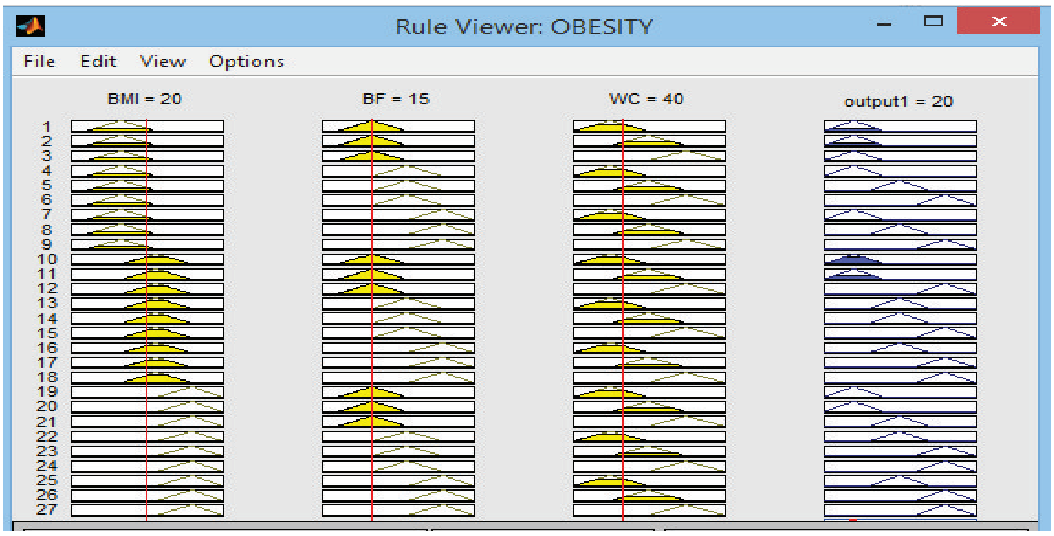


Figure 11: Graphical Construction of the Inference

Mechanism of Fuzzy Sets in Table 5

Assuming that, the fuzzy output, "healthy" value is 0.8, it indicates 80% possibility that the patient has normal weight and 20% possibility that he/she is overweight. If we consider the relationships strength among fuzzy, it indicates that it is only when "Overweight" output value equals 1.0, that we can conclude that the individual is overweight with 100% possibility.

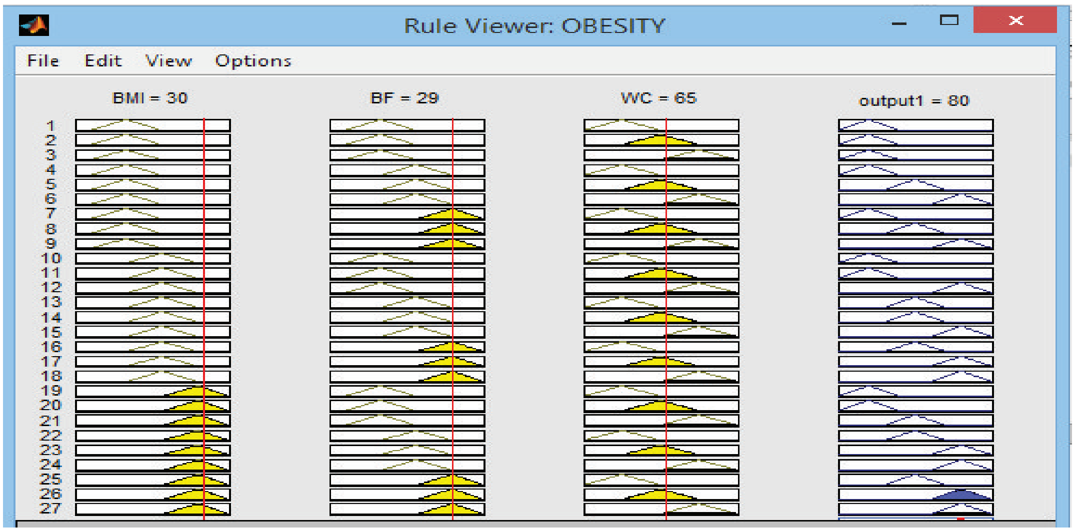


Figure 12: Graphical Construction of the Inference Mechanism of Fuzzy Sets in Table 6

For instance, if we relate "Healthy" with "Overweight", when the value of "Healthy" output is 0.70 showing 70% possibility, it indicates that there is 0.30 possibility of Overweight. This implies that it is not likely that the person is healthy altogether but 30% level of overweight. Relating "healthy" with "Overweight" with the relationship strength of 0.5 (50%), this indicates healthy level with 0.5 (50%) possibility and 0.5 (50%) of overweight as the case may be. Relating "Overweight" with "Obese" with the relationship strength of 0.4 (40%), it shows healthy level with 0.40 (40%) possibility and 0.60 (60%) of obese level. This result indicates that this patient is overweight with 40% possibility and he/she is obese with 60% level. Such person is referred to the doctor for advice.

Furthermore, we can observe several responses during the simulation of the system. Rules and membership functions can be modified through system tuning in order to achieve the desired output. The system can be widely applied by both male and female genders, those wanting to lose weight.

## 5. Conclusion

The study on obesity cannot be overemphasized due to the chronic diseases associated with it. Fuzzy logic techniques are becoming powerful enough to emulate an expert's choice due to their ability to handle robustness, imprecision and uncertainty, etc.  Fuzzy logic tool can obtain better results than classical approach. In this paper, we present a design methodology of fuzzy expert system in diagnosis and control of obesity. Fuzzy logic approach is used to find the exact degree of healthy, overweight and obese in obesity diagnosis in a patient. To this end, the proposed model can be used to diagnose, control and ensure the desired output since it can tolerate wide variation in input variables. Our model shows that obese level of obesity can be diagnosed at various degrees, but total obesity level is detected when the patient is 100% (1.0) obese. Also healthy level can be achieved at different levels based on a person's seemingly positive attitude towards food intake and exercise. The exact level and exact healthy, overweight and obese has been clearly defined by the system thereby resolving the conflict of uncertainty and vagueness. The system can be widely applied by both male and female genders, those wanting to lose weight. Our model will assist medical practitioners to diagnose and control the probable complications of obesity well in advance. In the future the study can be optimized by integrating it with neural network and particle swarm optimization tools.

## References

G. Eknoyan  "Adolphe Quetelet (1796-1874)–the average man and indices of obesity". Nephrol Dial Transplant, (23), pp 47-51, 2008.

D. Okorodudu, M.  Jumean, V. Montori, A. Romero-Corral, V. Somers, P. Erwin, F. Lopez-Jimenez  "Diagnostic performance of body mass indexto identify obesity as defined by body adiposity: a systematic review and meta-

analysis". Int J Obes, (34), pp 791-9, 2010.
T. Adams, E. Heath, M. LaMonte, R. Gress, R. Pendleton, M. Strong, S. Smith, S. Hunt "The relationship between body mass index and percent body fat in the severely obese". Diabetes Obes Metab, (9), pp 498-505, 2007.
S. Miyahira, J. Coutinho de Azevedo, and E. Araújo "Fuzzy obesity index (MAFOI) for obesity evaluation and bariatric surgery indication". Journal of Translational Medicine, 9:134, 1-10, 2011.
E. Rama Devi, N. Nagaveni "Design Methodology of a Fuzzy Knowledgebase System to predict the risk of Diabetic Nephropathy". IJCSI International Journal of Computer Science Issues, 7(5), pp 239-248, 2010.
B. Arunraj "Fuzzy Mathematical Modelling on the Control of Hypertrophic Obesity and Hyperplastic Obesity". International J. of Math. Sci. & Engg. Appls. (IJMSEA), 6(IV), pp. 77-90, 2011.
S. Margret Anouncia, L. Clara Madonna, P. Jeevitha, R. Nandhini "Design of a Diabetic Diagnosis System Using Rough Sets". Bulgarian Academy of Sciences Cybernetics and Information Technologies, 13(3), pp 124-140, 2013.
B. Poorna and K. Subith " Medical Diagnostic System using Fuzzy Logic". International Journal of Latest Trends in Engineering and Technology (IJLTET), 5(1), pp 307-311, 2015.
N. Manju Khanna and J. Mendiratta "The Study of Obesity in Children Using Fuzzy Logic". (Ijitr) International Journal of Innovative Technology and Research, 3(1), pp 1833 – 1836, 2015.
N. Nnamoko, F Arshad, D. England and J. Vora: Fuzzy Expert System for Type 2 Diabetes Mellitus (T2DM) Management Using Dual Inference Mechanism. Data Driven Wellness: From Self-Tracking to Behavior Change: Papers from the 2013 AAAI Spring Symposium, pp 67 – 71, 2013.
W. Ritha and W. Merline "Contributing factors and consequences of childhood obesity – An analysis using Induced Fuzzy Cognitive Maps (IFCMs)". Elixir Soc. Sci., (48), pp 9416-9419, 2012.
M. Ayilvaganan and K. Rajeswari "Analysis Study of Fuzzy Logic Using Blood Pressure Readings". International Journal of Computer & Organization Trends, 3(8), pp 302-306, 2013.
K. Cinetha and P. Maheswari "Decision Support System for Precluding Coronary Heart Disease using Fuzzy Logic. International Journal of Computer Science Trends and Technology (IJCST), 2(2), pp 102-108, 2014.
S. Mukhopadhyay and J. Ghosh "Studies on Fuzzy Logic and Dispositions for Medical Diagnosis". Int. J. Comp. Tech. Appl., 2 (5), pp 1235-1240, 2011.
A. Shora, M. Alam and R. Biswas "A Comparative Study of Fuzzy and Intuitionistic Fuzzy Techniques in a Knowledge based Decision Support" . International Journal of Computer Applications (0975 – 8887), 53(7), pp 13-17, 2012.
Y. Tong, J. Udupa, D. Odhner, S. Sin and R. Arens "Automatic Anatomy Recognition in Post-Tonsillectomy MR images of obese children with OSAS". Medical Imaging 2015: Computer-Aided Diagnosis, edited by Lubomir M. Hadjiiski, Georgia D. Tourassi, Proc. of SPIE Vol. 9414, 94140Z · © 2015 SPIE · CCC code: 1605-7422/15/$18 · doi: 10.1117/12.2081912.
C. Chin, R. Lin and S. Liu "Personal Healthy Diet and Calorie Monitoring System using Fuzzy Inference in Smart Phones". Medical Journal, (24), pp 49-60, 2013.
U. Umoh, E. Nwachukwu and O. Obot 'Fuzzy Rule-based Framework for Effective Control of Profitability in a Paper Recycling Plant". Global Journal of Computer Science and Technology (GJCST), (10), pp 56-67, 2010.
U. Umoh, E. Nwachukwu and O. Obot "Fuzzy-Neural Network Model for Effective Control of Profitability in a Paper Recycling Plant". American Journal of Scientific and Industrial Research (AJSIR). 2(4), pp 552-558, 2011.
K. Guney, 'Comparison of Mamdani And Sugeno Fuzzy Inference System Models For Resonant Frequency Calculation Of Rectangular Microstrip Antennas". Progress In Electromagnetics Research B, (12), pp 81–104, 2009.