RESEARCH ARTICLE OPEN ACCESS

A Type 2 Fuzzy Logic Based System for Basal Metabolic Rate Prediction of Diabetes Patients in Sudan

Heba Abdelgader Mohammed [1], Hani Hagras [2]
Department of Computer Science [1]
College of Postgraduate Studies, Sudan University of Science and Technology,
Sudan
The Computational Intelligence Centre [2], School of Computer Science and Electronic Engineering
University of Essex, Colcheste
U.K

ABSTRACT

Diabetes is a chronic disease which occurs mainly when the pancreas is unable to produce the amount of insulin that the human body requires or when the human body cannot successfully manage the insulin that has been produced. Various traditional methods, based on physical and chemical tests, are available for diagnosing this disease. A physical activity and a balanced diet are the best treatments for diabetes, and they can help patients avoid serious complications. Hence, there is a need to employ technologies to help diabetics and physicians control the disease and reduce its complications.

In artificial intelligence, the aspect of machine learning allows for the development of a computer system that can learn from experiences without having to be programmed for every instance. This paper presents a type-2 fuzzy-logic-based system to learn, from data a prediction model for Basal Metabolic Rate diabetes in Sudan which also allows to evaluate whether the rules used to calculate the amount of energy expended per day at rest (basal metabolic rate) for patients can help them to control the disease and achieve a healthy lifestyle.

Keywords* :— *Diabetes; Machine Learning; Type-2 Fuzzy Logic; Basal Metabolic Rate.

I. INTRODUCTION

Diabetes occurs when the level of blood glucose is too high. Blood glucose is the major source of our energy and is the main type of sugar in our blood. Glucose comes from the food we eat. The blood takes glucose to all our body's cells to use for energy. The pancreas delivers the hormone insulin to the blood. Insulin helps the blood carry glucose to all the body's cells. Sometimes the body does not make enough insulin, or the insulin does not work properly. The glucose then remains in the blood and does not move to the cells. This causes blood glucose levels to get too high and can cause diabetes[1]. As per the prediction of the World Health Organization (WHO), diabetes will be one of the major causes of death in 2030 and the death rate will double between 2005 and 2030[2]. Diabetes can cause physical inactivity and an unbalanced diet and seriously affect the patient’s lifestyle. Diabetes can be controlled through exercise, a balanced diet and proper medicine. [3]

There are three main types of diabetes:

- Type 1 diabetes: the body stops generating insulin or generates too little insulin to control the blood glucose level.
- Type 2 diabetes: the pancreas secretes insulin, but the body is unable to use the insulin.
- Gestational diabetes: This tends to occur during the 24^{th} week of pregnancy and happens when the body can't meet the extra insulin during pregnancy[3].

Diabetes of all types can lead to complications in many parts of the body and can increase the overall risk of premature death. Possible complications include heart attack, leg amputation, kidney failure, vision loss, stroke and nerve damage. In pregnancy, poorly controlled diabetes increases the risk of fetal death and other complications. Severe complications induced by diabetes can affect major organs of the body such as the heart, kidney, eyes and brain. The diagnosis of diabetes and its complication is determined using patients' symptoms and various pathological tests like urine, blood sugar, and lipid profile.

The complications of diabetes create life-threatening health problems, as high blood glucose levels can lead to serious diseases affecting the heart and blood vessels, kidneys, eyes and nerves[3]. Diabetes complications can be prevented by maintaining normal levels of blood glucose, blood pressure, and cholesterol and by consuming a balanced diet.

In 2019, a total of 463 million people was estimated to be living with diabetes, representing 9.3% of the global adult population (20–79 years). This number is expected to increase to 578 million (10.2%) in 2030 and to 700 million (10.9%) in 2045. The prevalence of diabetes among women in 2019 was estimated to be 9.0%, while the prevalence was estimated to be 9.6% in men (given by age group in Fig.1) [4]. The increase of diabetes prevalence with age leads to a prevalence of 19.9% (111.2 million) in people aged 65–79 years[4].

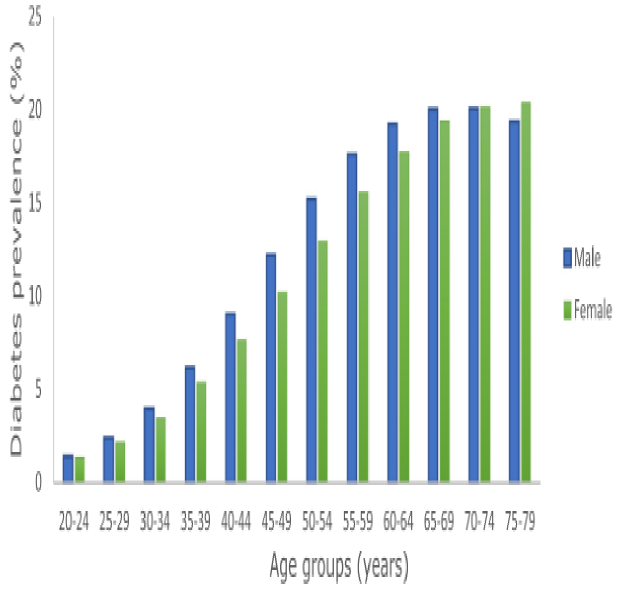

Fig.1.: Diabetes prevalence by age and sex in 2019 [4].

The Basal Metabolic Rate (BMR), defined as the energy required to perform vital body functions at rest, is the largest component of energy expenditure[5]. Several methods can be used to measure energy expenditure but there is no consensus as to which is the most accurate for specific populations. There are various factors to consider when calculating the basal metabolic rate, including age, gender, height, weight, and Body Mass Index (BMI). Because the BMR represents the major component of daily energy expenditure in humans, it is an important calculation for developing, understanding, and executing weight-related interventions[5].

The rest of the paper is organized as follows: Section II presents an overview of related work for diabetes recommendation systems. Section III presents an overview of the proposed type-2 fuzzy-logic-based system for Sudanese diabetics to learn, from data a prediction model for Basal Metabolic Rate diabetes which also allows to evaluate whether the rules used to calculate the amount of energy expended per day at rest (basal metabolic rate) for patients can help them achieve a healthy lifestyle to control the disease. Section IV presents the experiments and results. Section V presents the conclusions and future work.

II. RELATED WORK

We can improve an individual's lifestyle by using new technology and lead to behaviour changes that support the better management of diabetes and prevent or delay the development of complications [1]. In the past, much research has been carried out related in this area which could be categorized into Non-Artificial Intelligence, Artificial Intelligence, and Hybrid techniques. Some of the relevant studies are:

A. Non-Artificial Intelligence Techniques

There are several equations used to predict the basal metabolic rate developed by: Harris and Benedict, FAO/WHO/UNU, Owen et al., Mifflin et al., Huang et al., Gougeon et al., and Rodrigues et al.

The study in [5] compared the BMR estimated using the Harris-Benedict equation and BIA and the BMR measured using IC among adult obese Filipino patients with pre-diabetes or T2DM. The most widely used prediction equation is the Harris-Benedict Equation (HBE), which was developed in 1918 as a simple, easy-to-use, and universally available method for the calculation of BMR.

An ontology model based on interval type-2 fuzzy sets, called type-2 fuzzy ontology, for knowledge representation in the field of personal diabetic-diet recommendations was presented in[6].

In[7], it was shown that the resting metabolic rate (RMR) rate is higher in obese diabetic patients than in obese non-diabetic individuals. Predictive equations were unlikely to detect a difference in RMR between diabetic and non-diabetic subjects. The Mifflin equation is more reliable than the Harris-Benedict and FAO/WHO/UNU equations in terms of estimating RMR in obese diabetic patients.

In[8], the authors compared the seven equations to determine which of them most accurately estimate the BMR. They found that Owen et al.'s equation was closest to the measured basal metabolic rate.

Advantages/Pros of Non-Artificial Intelligence Techniques are Simplicity and Modularity

Disadvantages/Cons of Non-Artificial Intelligence Techniques are Ineffective search and Inability to learn.

B. Artificial Intelligence Techniques

The techniques used in artificial intelligence are divided into the categories of white box and black box. A black box is something that you can't see inside of. That is, it is unknown. A white box is the opposite; you can easily see the interior and observe exactly how it functions .

In[9], various optimization techniques used for the classification of diabetes depending on blood glucose level using fuzzy logic are reviewed. This system enhances recognition efficiency as compared to previously implemented techniques. A fuzzy expert system framework that effectively combines case-based and rule-based reasoning to produce a usable tool for type 2 diabetes mellitus (T2DM) management is proposed in[10].

The work in[11] focused on the development of a recommender system combing artificial intelligence techniques and making up a knowledge base according to the guidelines posed by the American Diabetes Association (ADA).

Advantages/Pros of White Box AI methods include: Transparency, Flexibility, Convenient user interface

Disadvantage/Cons of White Box AI methods include: Requires lots of data and expertise to develop, and Does not provide generalizable results

Advantages/Pros of Black Box AI methods include: Efficiency, Easy to understand, less time required for special application, and Separation between user's and developer's perspectives

Disadvantages/Cons of Black Box AI methods include Over-fitting and Lack of transparency.

C. Hybrid Techniques

In [12] and [13], a genetic fuzzy markup language (GFML)-based was presented including the genetic learning base, the knowledge base, and the rule base of the healthy diet domain, including the ingredients and the contained servings of six food categories of some common foods in Taiwan.

They also employed the fuzzy markup language (FML), which is a fuzzy-based markup language that can manage fuzzy concepts, fuzzy rules, and a fuzzy inference engine. It is based on the extensible markup language (XML) technology and its implementation exploits some typical XML tools such as the XML schema and the extensible style sheet language transformations (XSLT) [12] , [13] .

A method for predicting type 2 diabetes using the adaptive neuro-fuzzy interface system (ANFIS) with genetic algorithms (GA) was developed in[14].

Advantages/Pros of Hybrid Techniques AI methods include: Compact representation of general knowledge, Ability to express specialized knowledge, Modularity, and Efficiency

Disadvantages/Cons of Hybrid Techniques AI methods include: Knowledge acquisition bottleneck, Provision of explanations, and Difficulty maintaining large rule bases

From the above discussion, we can see that the recommendation systems for diabetes that do not employ artificial intelligence (AI) have ineffective search abilities and an inability to learn from data. On the other hand, the AI-based techniques are divided into white box and black box models. **White box** models require expertise to develop. **Black box** models do not allow for the generation of models that can be easily designed, analyzed, and interpreted by the diabetes patient and dietitian.

III. FUZZY LOGIC SYSTEM

A fuzzy logic system is unique in that it can handle linguistic knowledge and numerical data simultaneously. FLSs attempt to mimic human thinking. FLSs can play an main role in modeling and representing imprecise and uncertain linguistic human ideas [15].

Fuzzy logic is represented using fuzzy sets—sets that express uncertainty. Fuzzy logic is built on the concept of membership degrees and is designed to mathematically represent uncertainty for dealing with the inbuilt vagueness in some domains[15]. Normally, logic is comprised of only two values, i.e., true and false, and has constraints in terms of dealing with problems related to the real-world domain. Fuzzy logic uses logical values between 0 and 1[16].

The Fuzzy Inference System (FIS) is well known as a fuzzy expert system, a fuzzy model, or a fuzzy rule-based system. FIS is essentially a decision-making system that uses fuzzy logic or an IF-THEN rule for generating results. FIS is used mainly for uncertain and approximate reasoning. The architecture of the FIS model is given in Fig. 2 [17].

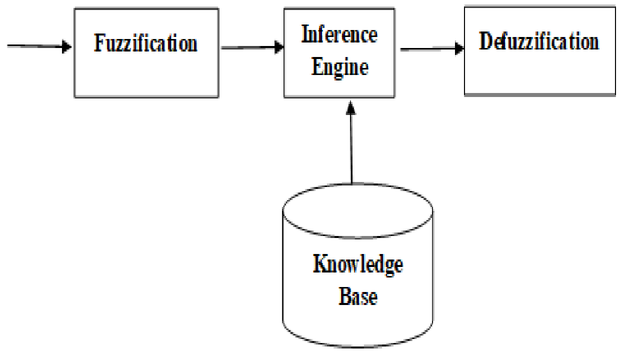

Fig. 2: Fuzzy inference system model [17]

The fuzzification unit converts the crisp value into a fuzzy value and provides it to the inference engine for decision-making. The inference engine extracts the appropriate data from the knowledge base as required by the fuzzy input value, performs the decision-making operations, and generates the fuzzy output value. The **defuzzification** unit converts the fuzzy output set into the crisp set as a result [17].

A. Type-1 Fuzzy Logic

Fuzzy logic was introduced by Lotfi Zadeh in 1965. It is based on the fuzzy set theory, which is an extension of the classical set theory and is a way of mathematically expressing the uncertainty of information. It can be regarded as a way of converting linguistic control information into mathematical control information[16].

Type-1 FLSs can operate well under specific operation conditions. Linguistic and numerical uncertainties can create problems in terms of determining the exact and precise antecedents and consequent membership functions during the FLS design. As time goes by, every user behavior and preference changes from one person to another; also, the domain experts' opinions vary[18]. Hence, the effectiveness of the type-1-based system declines when there are high uncertainty levels that are related to the diet domain for diabetes[19]. However, because of the environment changes and the associated uncertainties, the chosen type-1 fuzzy sets may no longer be appropriate. This can cause degradation in the FLS's performance, which can result in poor control and inefficiency, as well as lead to the wastage of resources spent on frequently redesigning or tuning the type-1 FLS (so that it can deal with the various uncertainties)[17].

B. Type-2 Fuzzy Logic

Type-2 fuzzy logic was introduced by Lotfi Zadeh in 1975. A type-2 fuzzy set is characterized by a fuzzy membership function, i.e., the membership value (or membership grade); each element of this set is a fuzzy set in [0, 1], unlike a type-1 fuzzy set, in which the membership grade is a crisp number in [0,1][20]. The membership functions of type-2 fuzzy sets are three-dimensional and include a footprint of uncertainty; the third dimension of type-2 fuzzy sets and the footprint of uncertainty are what provide additional degrees of freedom that make it possible to model and handle uncertainties[17].

Type-2 fuzzy logic is used to handle uncertain things coming from different opinions and to overcome the disadvantage of type-1 fuzzy logic[21]. Because the words mean different things to different people[22], T2FLS has the potential to provide better performance than a type-1 FLS (T1FLS) when such linguistic uncertainties are present [17].

.

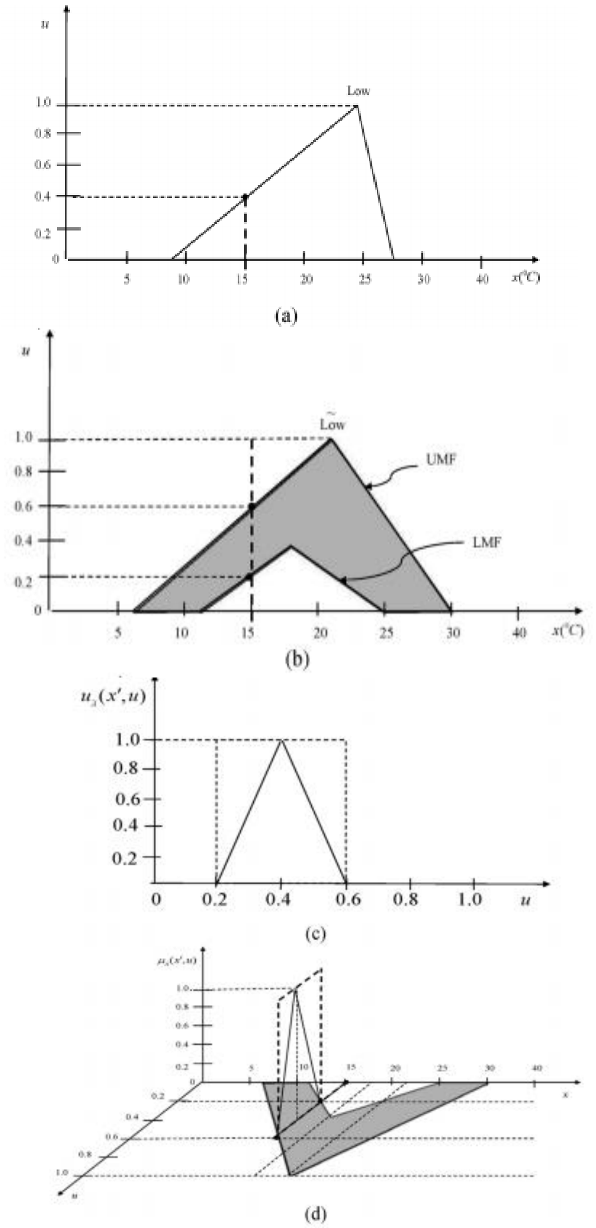

Fig. 3: (a) Type-1 FS (b) Type-2 FS-Primary MF (c) Type-2 FS-Secondary MF (d) Three-dimensional view of a T2FS[6]

There are various sources of uncertainty-involved in diet recommendation systems or applications[23] which could be classified as follows:

- Uncertainties associated with the changing behavior, context of the patient and exercise patterns.
- Uncertainties associated with sensed measurements and analysis associated with a diabetes patient are affected by the conditions of the measurements and the context of the diabetes patient.

As shown in Fig.3, the membership functions of type-2 fuzzy sets are three-dimensional and include a footprint of uncertainty

A fuzzy set A on a universe of discourse x is characterized by a membership function $\mu_A : x \rightarrow [0,1]$. The primary membership grade of a type-2 FLS is a Type-1 Fuzzy Set in [0, 1] and the secondary membership is a crisp number in [0, 1] [24]. The secondary membership function and the range of uncertainty are decided by the third dimension of type-2 fuzzy sets and footprint-of-uncertainty (FOU), respectively[25].

An Interval Type-2 Fuzzy Set $\tilde{A}$, is represented by the lower and upper membership functions of $\mu_A(x)$ where $x \epsilon X$ [26]

$$A = \{((x,u),1) \mid \forall u \in J_x \subseteq [0,1]\} \quad (1)$$

Where X is the primary domain and J_x is the secondary domain. All secondary grades ($\mu_{\tilde{A}}(x,u)$) are equal to 1[27].

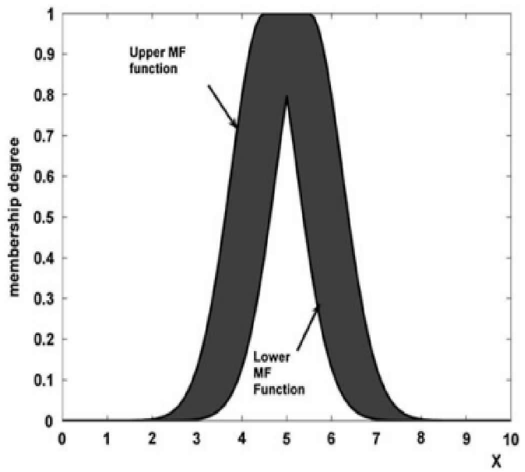

Fig. 4: Upper and lower membership functions[1]

As shown in Fig. 4, an upper MF and a lower MF are two type-1 MFs that are bounds for the footprint of the uncertainty of an interval type-2 MF. The upper MF is a subset that has the maximum membership grade of the footprint of uncertainty, while the lower MF is a subset that has the minimum membership grade of the footprint of uncertainty

As shown in Fig. 5, a type-2 FLS includes a fuzzifier, rule base, fuzzy inference engine, and output processor.

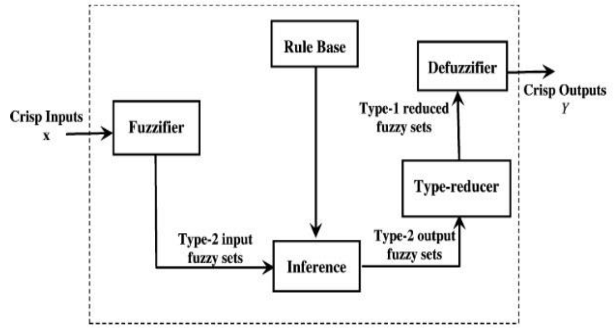

Fig. 5: Type-2 FLS[27]

The output processor includes a type-reducer and defuzzifier; it generates a type-1 fuzzy set output (from the type-reducer) or a crisp number (from the defuzzifier)[27].

IV. THE PROPOSED TYPE-2 FUZZY LOGIC SYSTEM FOR DIABETES MODELLING

We aim to develop a model that should generate from data models which could be easily analyzed and interpreted by the diabetes patient and the dietitian. The data was provided by diabetes centers in Sudan.

The proposed model (depicted on Fig. 6) will implement a type-2 fuzzy logic system for diabetes to help control this disease and reduce its complications. The purpose of the system is to calculate the amount of energy expended per day at rest (basal metabolic rate) to help patients achieve a healthy lifestyle that controls the disease.

The system should consider more than one parameter (such as gender, weight, height, age, and BMI) to determine the calories needed per day.

The proposed methodology for developing this system is to use type-2 fuzzy logic systems (FLSs) which have been credited with providing an adequate methodology for designing robust systems that are able to deliver satisfactory performance when contending with the uncertainty, noise, and imprecision attributed to real-world environments and applications.

A type-2 fuzzy set is characterized by a fuzzy membership function, i.e., the membership value for each element of this set is a fuzzy set in [0,1], unlike a type-1 fuzzy set, in which the membership value is a crisp number in [0,1][28]. The membership functions of type-2 fuzzy sets are three-dimensional and include a footprint of uncertainty (FOU) (which is shaded in Figure 4). The new third dimension of type-2 fuzzy sets and the FOU are what provide the additional degrees of freedom that make it possible to directly model and handle the uncertainties[29]. Type-2 fuzzy logic is used to handle uncertain concepts coming from different opinions and can overcome the disadvantages of type-1 fuzzy logic.

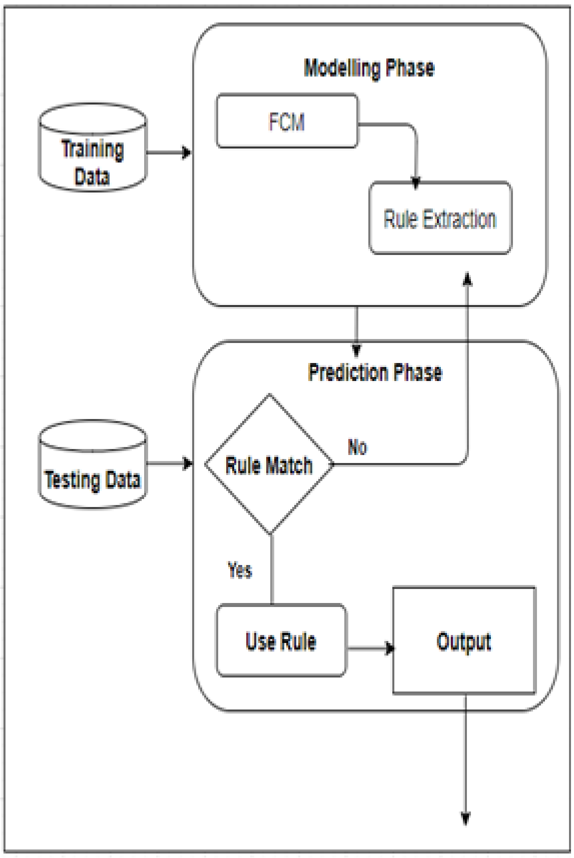

Fig. 6: Diagram for the proposed model

The proposed methodology is divided into two phases:
First Phase: Modeling Phase:
In this phase, there are two steps: **Fuzzy C-means Clustering and Fuzzy Rule Extraction.**
Fuzzy C-means Clustering:

Adapts the crisp input to a linguistic variable with the membership function gathered in the fuzzy knowledge base. We used the fuzzy c-mean clustering algorithm (FCM) to generate the membership function for the inputs petameter. FCM is one of the most widely used methods in fuzzy clustering that divides data into multiple clusters with different memberships and is a powerful unsupervised method for the analysis of data and the construction of models. In many situations, fuzzy clustering is more natural than hard clustering. The FCM provide work for fuzzy partitioning such that a data point can belong to all groups with different membership grades between 0 and 1[30].

This algorithm works by assigning membership to each data point corresponding to each cluster center, based on the distance between the cluster center and the data point. The closer the data is to the cluster center, the closer its membership is to the cluster center. Clearly, the summation of membership of each data point should be equal to one. After each iteration, membership and cluster centers are updated according to the formula.
The algorithm[30]:

1. Initialize $U = [u_{ij}]\, matrix, U^{(0)}$
2. At k-step: Calculate the centers vectors $C^{(k)} = [c_j]$ with $U^{(k)}$

$$C_i = \frac{\sum_{j=1}^{n} u_{ij}^{m} * j}{\sum_{j=1}^{n} u_{ij}^{m}} \qquad (2)$$

3. Update $U^{(k)}, U^{(k+1)}$
4. $d_{ij} = \sqrt{\sum_{i=1}^{n} (x_i - c_i)}$ (3)

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \qquad (4)$$

5. $if \parallel U(k+1) - U(k) \parallel < \in then\ Stop;$ otherwise, return to step 2.

Here [31]

m is any real number greater than 1,

u_{ij} is the degree of membership of x_i in cluster j,

x_i is the $_i$th of the d-dimensional measured data, and

c_j is the d-dimension center of the cluster

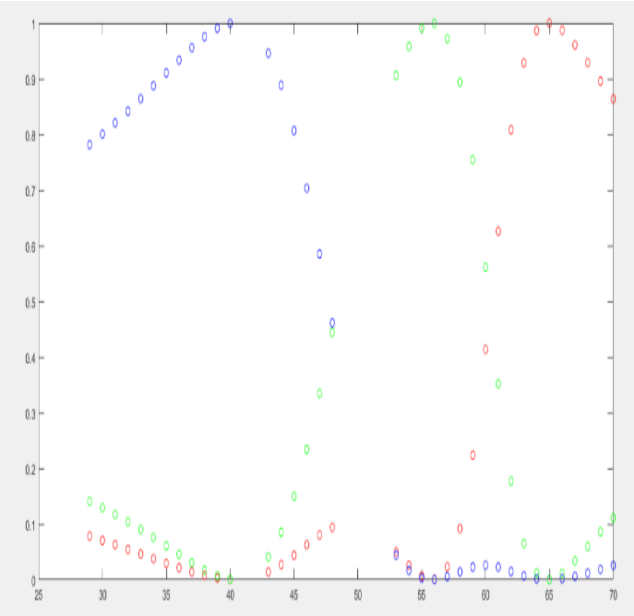

Fig. 7: Sample of an FCM fuzzy set for age

The extracted clustering from the FCM is shown in in Fig. 7 before we change it to type-1 fuzzy sets (in Fig. 8) and type-2 fuzzy sets.

The sample of a type-1 fuzzy set is shown in Fig. 8.

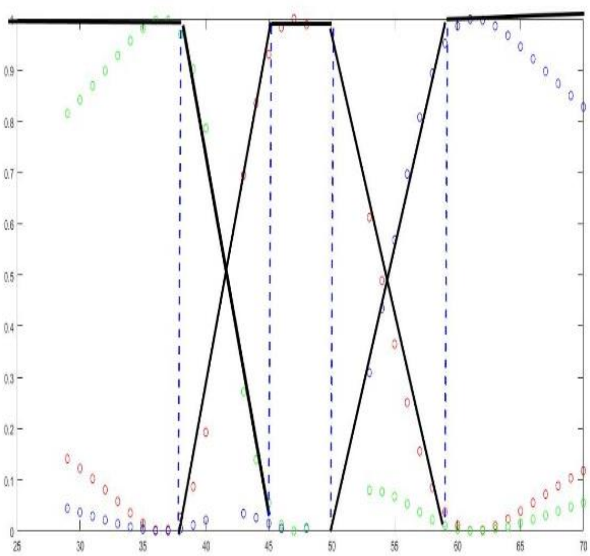

Fig. 8: Type-1 fuzzy set for age

The sample of a type-2 fuzzy set with 10% FOU is shown in Fig. 9.

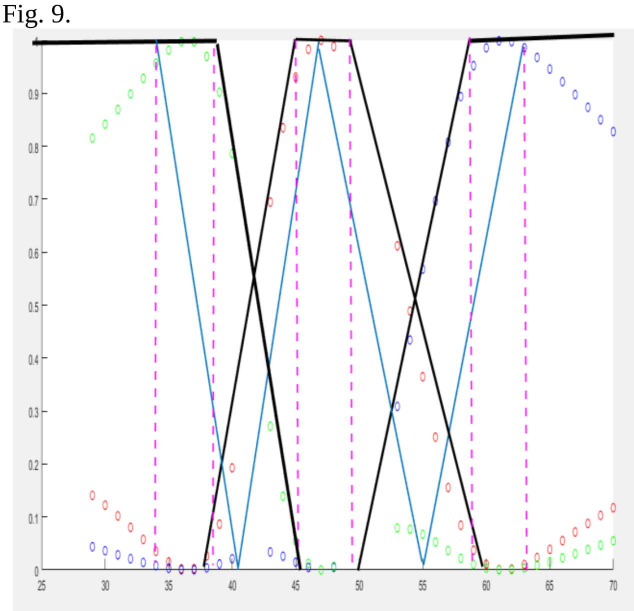

Fig. 9: Type-2 fuzzy set for age

Fuzzy Rule Extraction:

If-then-type fuzzy rules change the fuzzy input into the fuzzy output. The inference engine combines rules and gives a mapping from input type-2 sets to output type-2 sets[32].

From the training data set that contains the number of records with the input and output pair (x(n), Y(n)), n=1, N (N is the number of records in the data set).

- Calculate the upper and lower membership values for each record $(\overline{\mu}_{A_i^j}, \underline{\mu}_{A_i^j})$, $j=1,\ldots n$ (n is the total number of fuzzy sets for input I where $I = 1, \ldots n$)

- Calculating center of gravity for each upper and lower fuzzy set [21]

$$cg = \frac{\overline{\mu}_{A_i^j} + \underline{\mu}_{A_i^j}}{2} \quad (5)$$

- Calculating weight by selecting the max value between Center of gravity for fuzzy set.
- Calculating the strength of the point *(x(n))* belong to which fuzzy set we need to find firing strength which is defined with lower and upper$(\underline{f}^{(t)}, \overline{f}^{(t)})$

$$\underline{f}^{jt}(x^{(t)}) = \underline{\mu_{A_1^{qjt}}}(x_1) * \dots * \underline{\mu_{A_n^{qjt}}}(x_n) \quad (6)$$

$$\overline{f}^{jt}(x^{(t)}) = \overline{\mu_{A_1^{qjt}}}(x_1) * \dots * \overline{\mu_{A_n^{qjt}}}(x_n) \quad (7)$$

Where * represent product or minimum t-norm.

- Generate all the possible rules. The number of rules should be the same as the number of records. The rule can be written as follows for each pair of input-output pair (x(n), Y(n)):

$$R_i : If\ x_1\ is\ A_1\ and \dots and\ x_n\ is\ A_n\ then\ output\ Y_n\ , n = 1, \dots n \quad (8)$$

Example of rule generated:

***If Age** is Old and **Gender** is Male and **Type of Diabetes** is Type 2 and **BMI** is Under Weight and **Management** is Tablet and **Height** is Long and **Weight** is Slight Then **Outcome BMR** is Low.*

Second Phase: Prediction Phase:

Now we have a system with a type-2 fuzzy logic system and we can accept any new input to predict the output.

Type Reduction:

This takes us from the type-2 output sets of the inference engine to a type-1 set that is called the "the type-reduced set". The calculation of the type-reduced sets is divided into two stages[27] [15].

The first stage is the calculation of centroids of the rule consequents:[33] For any output, the type-2 interval consequent set of the ith rule will be one of the output type-2 interval fuzzy sets representing this output then the centroid of the type-2 interval consequent set for the i[th] rule y_k^i will be one of the precalculated centroids of the type-2 output sets y_k^i which corresponds to the rule consequent.

The second stage to calculate the type-reduced sets which are then defuzzified to produce the crisp outputs. For any output k we need to compute y we need to compute its two end points y_{lk} and y_{rk} For each rule, we need to attach to the firing strength $f^i$the centroid of the th rule consquent calculated in the previous step.

$$y_{lk} = \frac{\sum_{i=1}^{M} f_l^i f y_{lk}^i}{\sum_{i=1}^{M} f_l^i} \quad (9)$$

$$y_{rk} = \frac{\sum_{i=1}^{M} f_r^i f y_{rk}^i}{\sum_{i=1}^{M} f_r^i} \quad (10)$$

Defuzzification:

This changes the fuzzy output of the inference engine to crisp using the membership function equivalent to the fuzzifier. The centroid method is used to convert the final combined fuzzy conclusion into a crisp value [16] [23].

From the type-reduction stage, we have, for each output, a type-reduced set Y determined by its left-most point Y_{lk} and its right-most point Y_{rk}. We defuzzify the interval set by using the average of Y_{lk} and Y_{rk}. Hence, the defuzzified crisp output for each output is

$$Y_k\ (x) = \frac{Y_{lk} + Y_{rk}}{2} \quad (11)$$

V. EXPERIMENTS AND RESULTS

To compare and validate the findings, the system was tested on the data set collected from Jabir Abu-Eliz Center in Khartoum. This dataset contains 700 instances and seven attributes. The dataset is divided into two sets: a training dataset with 70% of data and a testing dataset with 30% of data.

The training dataset is used to generate the fuzzy model parameters (i.e rules and fuzzy sets). The classification accuracy of the proposed system was evaluated on the testing data.

The input attributes are age, gender, type of diabetes, body mass index (BMI), management, weight, and height. the output of the system is the basal metabolic rate (BMR). The inputs and outputs of the model are :

Age:Age has three fuzzy sets: Young, Middle Age, and Old.

Gender: Either Male or Female.

Type of diabetes: Either Type 1 or Type 2.

Body Mass Index (BMI): BMI is considered an assessment that evaluates the weight of the body in relation to the height of the body. This attribute contains three fuzzy sets in the developed system: Under Weight, Normal, and Over Weight.

Management: Either Tablet, Insulin, or Diet Control.

Height: Either Short, Normal, or Long.

Weight: Eight Slight, Normal, or Heavy.

Output BMR: Basal metabolic rate is the amount of energy expended per day at rest.

Input Parameters	*Linguistic Variables*
1. Age	Young
	Mid-age
	Old
2. Gender	Male
	Female
3. Type of Diabetes	Type1
	Type2

4.	Body Mass Index (BMI)	Under Weight
		Normal
		Over Weight
5.	Management	Tablet
		Insulin
		Diet Control
6.	Height	Short
		Normal
		Long
7.	Weight	Slight
		Normal
		Heavy

Table 1: Input variables and associated fuzzy set classifications

Output Parameters	***Fuzzy Set Classifications and Their Range***
Output Calories	Low
	Medium
	High

Table 2: Output variables and associated fuzzy set classifications

The type-2 fuzzy system was compared to a type-1 fuzzy based system.
Fig. 10 show the system user interfaces which accepts the new input (age, gender, type of diabetes, management, weight, height, and BMI) and then predicts, for the patient, the output BMR amount of energy expended per day.

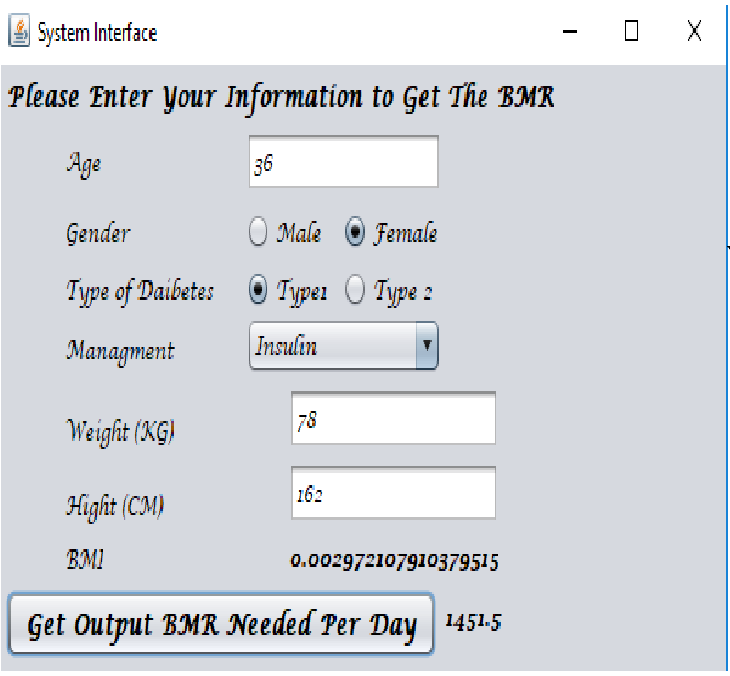

Fig. 100: The proposed system with patient data

The Root Mean Square Error (RMSE) method was used to measure the proposed model accuracy[34] as follows:
We can compare The root mean square

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \qquad (12)$$

P_i is the actual measurement and O_i is the observed value. From Table 3, we see that the type-2 fuzzy based system with FOU 10% is better than type-1 fuzzy system by 28.12%.

Classifier	***Result***	
Type-1 Fuzzy Logic	***With FCM***	***Without FCM***
	0.73	*0.75*
Type-2 Fuzzy Logic with FCM	***FOU10%***	***FOU20%***
	0.55	*0.59*

Table 3: RMSE Results

Table 4 shows examples of the extracted rules where rule **R1** indicates that a mid-age Female with type 2 diabetes with BMI is under weight is likely to take high Basal Metabolic Rate. Rule **R2** refers that an old age is male with type 1 diabetes with BMI under weight is most likely to have Medium Basal Metabolic Rate.

R1	If ***Age*** is Mid-age and ***Gender*** is Female and ***Type of Diabetes*** is Type 2 and ***BMI*** is Under Weight and ***Management*** is Tablet and ***Hight*** is Long and ***Wight*** is Slight Then ***Outcome BMR*** is High
R2	If ***Age*** is Old and ***Gender*** is Male and ***Type of Diabetes*** is Type 1 and ***BMI*** is Under Weight and ***Management*** is Insulin and ***Hight*** is Long and ***Wight*** is Slight Then ***Outcome BMR*** is Medium

Table 4: Examples of Extracted Rule.

Therefore, by analyzing these rules, this information can help to develop an APP that give the patient in Sudan list of food choices based on the calories needed per day according to their personal food preference and daily activities.

VI. CONCLUSIONS

The occurrence of diabetes is increasing rapidly, as in 2019, a total of 463 million people was estimated to be living with diabetes, representing 9.3% of the global adult population (20–79 years). This number is expected to increase to 578 million (10.2%) in 2030 and to 700 million (10.9%) in 2045. The amount of energy expended is an important element in the estimation of energy requirements. In addition to its importance in scientific research, it has become an essential tool in the maintenance of a healthy body weight. physical activity and a balanced diet are the best treatments for diabetes and can help patients avoid serious complications. Hence, there is a need to employ technology to help diabetics and doctors control the disease and reduce its complications. Various techniques have been employed for diabetes control. However, there is a need for a technique that handles the uncertainties associated with people's varied opinions and preferences.

Several authors have shown that the equations for predicting or calculating BMR can generate errors that overestimate or underestimate the result, without, however, clarifying the magnitude of these errors. This paper presented a type-2 fuzzy-logic-based system to learn, from data a prediction model for Basal Metabolic Rate diabetes in Sudan which also allows to evaluate whether the rules used to calculate the amount of energy expended per day at rest (basal metabolic rate) for patients can help them achieve a healthy lifestyle to control the disease. The proposed system did outperform their type-1 fuzzy based counterparts by a 28% better RMSE. The extracted rules can shed light on Sudanese diabetes patients output BMR which will be used in our future work to provide advice on the daily diet and activities to diabetes patients in Sudan.

REFERENCES

[1] H. A. Mohammed and H. Hagras, "Towards Developing Type 2 Fuzzy Logic Diet Recommendation System for Diabetes," *2018 10th Comput. Sci. Electron. Eng. Conf. CEEC 2018 - Proc.*, pp. 56–59, 2019.

[2] H. Das, B. Naik, and H. S. Behera, *Classi fi cation of Diabetes Mellitus Disease (DMD): A Data Mining (DM) Approach*, no. Dmd. Springer Singapore, 2018.

[3] R. P. Ambilwade, R. R. Manza, and R. Kaur, "Prediction of Diabetes Mellitus and its Complications using Fuzzy Inference System," vol. 6, no. 7, 2016.

[4] P. Saeedi *et al.*, "Global and regional diabetes prevalence estimates for 2019 and projections for 2030 and 2045: Results from the International Diabetes Federation Diabetes Atlas, 9th edition," *Diabetes Res. Clin. Pract.*, vol. 157, p. 107843, 2019.

[5] S. C. R. Luy and O. A. Dampil, "Comparison of the harris-benedict equation, bioelectrical impedance analysis, and indirect calorimetry for measurement of basal metabolic rate among adult obese filipino patients with prediabetes or type 2 diabetes mellitus," *J. ASEAN Fed. Endocr. Soc.*, vol. 33, no. 2, pp. 152–159, 2018.

[6] C. S. Lee, M. H. Wang, and H. Hagras, "A type-2 fuzzy ontology and its application to personal diabetic-diet recommendation," *IEEE Trans. Fuzzy Syst.*, vol. 18, no. 2, pp. 374–395, 2010.

[7] T. H. Merghani, "Measured Versus Predicted Resting Metabolic Rate in Obese Diabetic and Obese Non-Diabetic Subjects," *IOSR J. Dent. Med. Sci.*, vol. 10, no. 2, pp. 63–67, 2013.

[8] M. De Figueiredo Ferreira *et al.*, "Body composition and basal metabolic rate in women with type 2 diabetes mellitus," *J. Nutr. Metab.*, vol. 2014, pp. 7–9, 2014.

[9] A. Rungta and T. Nadu, "A Review on Classification of Diabetes using Fuzzy Logic and Optimization Technique," vol. 13, no. 8, pp. 2143–2150, 2017.

[10] N. Nnamoko, F. Arshad, D. England, and P. J. Vora, "Fuzzy Expert System for Type 2 Diabetes Mellitus (T2DM) Management Using Fuzzy Expert System for Type 2 Diabetes Mellitus (T2DM) Management Using Dual Inference Mechanism," no. May 2014, 2013.

[11] S. Norouzi *et al.*, "A mobile application for managing diabetic patients' nutrition: A food recommender system," *Arch. Iran. Med.*, vol. 21, no. 10, pp. 466–472, 2018.

[12] M.Kalpana and A. . S. Kumar, "Design and implementation of Fuzzy Expert System using Fuzzy Assessment Methodology," *Int. J. Sci. Appl. Inf. Technol.*, vol. 1, no. 1, pp. 39–45, 2012.

[13] H. Hagras, F. Doctor, V. Callaghan, and A. Lopez, "An incremental adaptive life long learning approach for type-2 fuzzy embedded agents in ambient intelligent environments," *IEEE Trans. Fuzzy Syst.*, vol. 15, no. 1, pp. 41–55, 2007.

[14] S. Alby, "A prediction model for type 2 diabetes using adaptive neuro-fuzzy interface system .," 2018.

[15] A. Sakalli, T. Kumbasar, E. Yesil, and H. Hagras, "Analysis of the performances of type-1, self-tuning type-1 and interval type-2 fuzzy PID controllers on the Magnetic Levitation system," *IEEE Int. Conf. Fuzzy Syst.*, no. March 2016, pp. 1859–1866, 2014.

[16] J. M. Mendel, "Fuzzy Logic Systems for Engineering: A Tutorial," *Proc. IEEE*, vol. 83, no. 3, pp. 345–377, 1995.

[17] H. Hagras and C. Wagner, "Towards the Wide Spread Use of Type-2 Fuzzy Logic Systems in Real World Applications," no. August, pp. 14–24, 2012.

[18] M. S. E. Alhassan and H. Hagras, "Towards Congestion Control Approach Based on Weighted Random Early Detection and Type-2 Fuzzy Logic System," *2018 10th Comput. Sci. Electron. Eng. Conf. CEEC 2018 - Proc.*, pp. 71–74, 2019.

[19] V. Shital and S. S. Sambare, "Study of Diet Recommendation System based on Fuzzy Logic and Ontology," *Int. J. Comput. Appl.*, vol. 132, no. 12, pp. 20–24, 2015.

[20] H. S. Yusuf and H. Hagras, "Towards Image Steganography Using Type-2 Fuzzy Logic and Edge Detection," *2018 10th Comput. Sci. Electron. Eng. Conf. CEEC 2018 - Proc.*, pp. 75–78, 2019.

[21] A. Starkey, H. Hagras, S. Shakya, and G. Owusu, "IPatch: A Many-Objective Type-2 Fuzzy Logic System for Field Workforce Optimization," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 3, pp. 502–514, 2019.

[22] Y. W. Chen and C. J. Lin, "Studies in Fuzziness and Soft Computing," *Featur. Extr. Found. Appl.*, vol. 207/2006, pp. 315–324, 2006.

[23] A. Starkey, H. Hagras, S. Shakya, and G. Owusu, "A multi-objective genetic type-2 fuzzy logic based system for mobile field workforce area optimization," *Inf. Sci. (Ny).*, vol. 329, pp. 390–411, 2016.

[24] S. S.-J. of E. and C. Science and undefined 2019, "A Fraud-Detection Fuzzy Logic Based System for the Sudanese Financial Sector," *Journal.Sustech.Edu*, vol.

20, no. 1, 2019.

[25] K. A. Naik and C. P. Gupta, “Performance comparison of Type-1 and Type-2 fuzzy logic systems,” *4th IEEE Int. Conf. Signal Process. Comput. Control. ISPCC 2017*, vol. 2017-Janua, pp. 72–76, 2017.

[26] O. Castillo, L. Amador-Angulo, J. R. Castro, and M. Garcia-Valdez, “A comparative study of type-1 fuzzy logic systems, interval type-2 fuzzy logic systems and generalized type-2 fuzzy logic systems in control problems,” *Inf. Sci. (Ny).*, vol. 354, pp. 257–274, 2016.

[27] H. A. Hagras, “A Hierarchical Type-2 Fuzzy Logic Control Architecture for Autonomous Mobile Robots,” vol. 12, no. 4, pp. 524–539, 2004.

[28] H. Hagras, “Employing computational intelligence to generate more intelligent and energy efficient living spaces,” *Int. J. Autom. Comput.*, vol. 5, no. 1, pp. 1–9, 2008.

[29] B. Yao, H. Hagras, D. Alghazzawi, and M. J. Alhaddad, “A big bang-big crunch type-2 fuzzy logic system for machine-vision-based event detection and summarization in real-world ambient-assisted living,” *IEEE Trans. Fuzzy Syst.*, vol. 24, no. 6, pp. 1307–1319, 2016.

[30] R. Suganya and R. Shanthi, “Fuzzy C-Means Algorithm-A Review,” *Int. J. Sci. Res. Publ.*, vol. 2, no. 11, pp. 2250–3153, 2012.

[31] R. Chaieb, K. Kalti, M. M. Luqman, M. Coustaty, J. M. Ogier, and N. Essoukri Ben Amara, “Fuzzy generalized median graphs computation: Application to content-based document retrieval,” *Pattern Recognit.*, vol. 72, pp. 266–284, 2017.

[32] K. Almohammadi and H. Hagras, “An interval type-2 fuzzy logic based system for customised knowledge delivery within pervasive elearning platforms,” *Proc. - 2013 IEEE Int. Conf. Syst. Man, Cybern. SMC 2013*, pp. 2872–2879, 2013.

[33] J. D. Barrett, *Advanced Fuzzy Logic Technologies in Industrial Applications*, vol. 49, no. 4. 2007.

[34] T. Chai and R. R. Draxler, “Root mean square error (RMSE) or mean absolute error (MAE)? -Arguments against avoiding RMSE in the literature,” *Geosci. Model Dev.*, vol. 7, no. 3, pp. 1247–1250, 2014.