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# Type-2 fuzzy ontology–aided recommendation systems for IoT–based healthcare

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A R T I C L E I N F O

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A B S T R A C T

The number of people with a chronic disease is rapidly increasing, giving the healthcare industry more challenging problems. To date, there exist several ontology and IoT-based healthcare systems to intelligently supervise the chronic patients for long-term care. The central purposes of these systems are to reduce the volume of manual work in recommendation systems. However, due to the increase of risk and uncertain factors of the diabetes patients, these healthcare systems cannot be utilized to extract precise physiological information about patient. Further, the existing ontology-based approaches cannot extract optimal membership value of risk factors; thus, it provides poor results. In this regards, this paper presents a type-2 fuzzy ontology–aided recommendation systems for IoT-based healthcare to efficiently monitor the patient's body while recommending diets with specific foods and drugs. The proposed system extracts the values of patient risk factors, determines the patient's health condition via wearable sensors, and then recommends diabetes-specific prescriptions for a smart medicine box and food for a smart refrigerator. The combination of type-2 Fuzzy Logic (T2FL) and the fuzzy ontology significantly increases the prediction accuracy of a patient's condition and the precision rate for drug and food recommendations. Information about the patient's disease history, foods consumed, and drugs prescribed is designed in the ontology to deliver decision-making knowledge using Protégé Web Ontology Language (OWL)-2 tools. Semantic Web Rule Language (SWRL) rules and fuzzy logic are employed to automate the recommendation process. Moreover, Description Logic (DL) and Simple Protocol and RDF Query Language (SPARQL) queries are used to evaluate the ontology. The experimental results show that the proposed system is efficient for patient risk factors extraction and diabetes prescriptions.

## 1. Introduction

In recent years, the healthcare industry has faced significant pressure due to the continuous increase in patients with chronic diseases and their long-term medical treatment. Many clinical applications have been proposed to overcome the load of chronic patients in hospital [1–4]. However, the escalation in the number of diabetes patients and their risk factors may create confusion for physicians wishing to automatically extract physiological information for diagnoses. Furthermore, elderly patients with chronic diseases are unable to continuously visit physicians, which is in turn both inappropriate and costly [5,6]. A wearable sensor-based healthcare monitoring service via the Internet of Things (IoT) is more effective for long-term medical care, and for clinical access to extract precise physiological information about patients and for disease management [7]. However, the existing healthcare systems are inefficient at extracting accurate membership values for physical parameters of the patient's body, because most of the healthcare systems use conventional technologies and approaches, such as risk score calculators, a classic ontology, and fuzzy logic [8].

Dietary control and precise diabetes drug recommendations are another problem for the existing IoT-based healthcare monitoring architecture [9]. Nowadays, diabetes patients use existing systems or consult with a nutrition expert to know a food's nutritional value. These existing systems are unable to provide precise information on

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nutritional diets without knowing the current physiological information about the diabetes patient, which can worsen the patient's condition. Diabetes patients access nutrition expert facilities when their blood glucose levels suddenly rise due to a lack of knowledge about the nutrient levels in the foods they eat. In addition, it is difficult for experts to extract all the risk factors about patients and to obtain meaningful information regarding their needs with regard to foods and drugs. Generally, the risk factors of a diabetes patient are unpredictable; where a drug or food type varies for every patient, depending on the patient's current condition. Both healthcare treatment and recommendations have complexity and uncertainty. One recent useful technique is fuzzy ontology–based semantic knowledge, which can help to address the uncertainty in healthcare monitoring and recommendation systems.

Healthcare monitoring and recommendation systems are mostly based on a classic ontology [10–12]. Classic ontologies address crisp data, which cannot address imprecise and vague knowledge about diabetes diagnoses. Therefore, fuzzy logic is incorporated with the classic ontology (called a fuzzy ontology). Recently, fuzzy logic with an ontology has been proposed in several systems to better diagnose diabetes [8,13]. However, a greater variety of foods is available, which is associated with a higher risk for diabetes, and the number of diabetes patients and the risk factors are rapidly increasing. Type-1 fuzzy logic–based systems cannot extract precise membership values because most of the risk factors are intensively blurred and unpredictable; thus, the systems provide poor results. Therefore, type-2 fuzzy logic with a fuzzy ontology is considered effective technology for detecting precise physiological information about a patient's body and for recommending diabetes treatments.

To overcome these problems, this paper proposes type-2 fuzzy logic and fuzzy ontology–based decision-making knowledge to automate the overall processes of foods and drugs recommendation for IoT-healthcare systems. This proposed system contains two layers: a security layer and a type-2 fuzzy ontology–based decision-making knowledge layer. The security layer prevents unauthorized access to a smart refrigerator and medical devices, and investigates the true condition of the right patient before the recommendation of foods and drugs. The type-2 fuzzy ontology–based semantic knowledge layer extracts the patient risk factor values via wearable sensors, determines the patient's health condition using type-2 fuzzy logic, retrieves drug and food information from the fuzzy ontology, and then recommends prescription for a smart medicine box and foods for a smart refrigerator, according to the patient's condition. This paper is organized as follows. Section 2 provides a summary of the existing research works. In Section 3, the basic concepts of type-2 fuzzy logic-based health condition declaration are given. Whereas Section 4 explains the overall scenario and the internal process of the proposed architecture, Type-2 fuzzy ontology–based semantic knowledge and the recommendation systems are explained in Section 5. In Section 6, the experiments of ontology-based patient monitoring and their results are discussed. The last Section concludes this paper.

## 2. Research works

Nowadays, many technologies are in use to support healthcare systems for chronic patient monitoring and diagnosis [14,15]. However, a rapid increase in the number of chronic patients and associated risk factors has made the healthcare monitoring system more challenging. The current trend in this area is that the people keep track of their health risk scores by using various online and offline healthcare systems, such as those offered by the American Diabetes Association, Diabetes Australia, QDiabetes and CANRISK [16]. Most of these online systems work based on risk score calculators and the backend methods are quite naive. Therefore, such calculators are unable to extract all the risk factors to diagnose diabetes. These risk factors are collected in a classic format for numerical factors and a string format for categorical factors. Smart methodological work is needed to automatically extract data about a diabetes patient's body, compute the risk value, and recommend drugs and foods. Researchers have been working on these issues and have proposed several solutions for diabetes diagnosis [17–19].

The IoT and wearable monitoring system is an emerging technology that is expected to contribute a wide range of healthcare applications in the future [2,3,9,20,21]. A system to capture physiological data of a person under care using IoT sensors was presented by Chiang and Liang [8]. This system combined a context-aware space with IoT technology to automate healthcare services and assist chronic patients. The main problem with their method is that when the chronic patient risk factors increase, the system is unable to find the correct risk value. In addition, a classic ontology approach is not useful in supporting a fuzzy logic–based system during information extraction from an uncertain patient disease history and unknown risk factors. The Mamdani inference method is used for heart disease diagnosis [22]. This system has 13 input features and one output feature in order to find the presence of heart disease in a patient. However, the existing system needs semantic knowledge that is specific to each disease. An analysis of heart rate variability signals is computed using fuzzy measure entropy (FuzzyMEn) [23]. The system overcomes the poor statistical stability of two entropy measures, which are based on the Heaviside step function of the classical sets. This system used fuzzy logic instead of Heaviside, and achieved better results than approximate entropy (ApEn) and sample entropy (SampEn). Kumar and Kaur used a fuzzy expert system to detect heart disease in patients [24]. This system contains six input fields (blood pressure, cholesterol, chest pain type, maximum heart rate, blood sugar, and old peak) and two output fields (heart disease and precautions). However, this system is insufficient in terms of factors and semantic relationships amongst the patient's medical data. A computational intelligence model based on fuzzy logic was proposed to handle ambiguity and vagueness in clinical knowledge and data [25]. This method overcomes the interpretation problem of the common monitoring system called a cardiotocograph (CTG), which is based on a fetal heart rate pattern and maternal contraction. A fuzzy logic–based method for fault-tolerant wireless sensor networks was proposed to monitor diagnosis and testing systems in a large-scale context [26]. However, a large storage space in the IoT is used when small movement is detected by a sensor. The mentioned method extracts limited information because of limited semantic knowledge. A single ontology is insufficient to tolerate the IoT's faults. It is important to make multiple ontologies for diagnosis and testing, which can provide intelligent knowledge to retrieve precise data for fault-tolerance problems in the IoT. A fuzzy approach was used in an IoT-based healthcare monitoring system to find abnormal conditions in a patient [27]. This system helps a physician to select the affected parameters and avoids unnecessary information transmission to the physician. A fuzzy logic and thermistor sensor–based approach was proposed for monitoring and early detection of residential fire [28]. This proposed system uses two fuzzy methods with temporal characteristics to monitor and determine confidence about the presence of fire in order to decrease and improve the number of rules that are employed to make correct decisions. A model driven approach was presented to design and develop smart IoT-based system [29]. A set of design pattern is defined in this method to syndicate cognitive and autonomic principals for providing a precise solution according to the system needs. A fuzzy prolog and ontology-based framework was proposed to detect health anomalies in real-time using IoT devices [30]. This existing ontology gives hints about diseases that are currently going on. However, simple ontology may not be able to handle real-time sensor's data for having a complete detail of a patient. Wearable devices with solar-energy harvesting were presented to ease the implementation of an autonomous wireless body area network (WBAN) [31]. Different sensors are employed on various positions of the body to measure the heartbeat, temperature, and to detect falls. The data from sensors and fall notification is shown through web-based smart phone application. Systems based on wearable healthcare devices were reviewed both in commercial efforts and scientific papers

[32–34]. This review determined the design architecture of IoT in the medical field, including software and hardware dealing with sensors, medical application, and smart phones for diagnosis. A gateway between sensor network and the Internet in IoT-based healthcare system was proposed to translate the protocols used in sensor network and the Internet [35]. This gateway contains control knowledge for both the sensor network and the data transmitted through the Internet in healthcare IoT system.

The performance of ontology has been extensively investigated in the fields of healthcare and the IoT environment [11,36]. An ontology-based public healthcare system for the IoT was proposed to overcome security and privacy challenges in a healthcare information system [10]. The system provides a way to collect, integrate, and interoperate via the IoT during an emergency. However, the hospitals' data are almost always uncertain, and a classic ontology is unable to retrieve patient information efficiently. For example, a patient's condition maybe normal, good, or satisfactory, and the service may be fast, normal, or slow; the doctor may be busy, free, or unavailable. Therefore, a fuzzy ontology is needed to classify every point of the healthcare system for emergency medical–information sharing. A drug discovery investigation (DDI)-based ontology was proposed to assign a value to the information created during drug discovery in order to make it easier to reuse, retrieve, and integrate the created information. [37]. This proposed DDI system Ontology-based healthcare knowledge was produced to support clinical decisions for chronically ill patients. This system presents two personalized processes and a decision support tool. The first personalized process uses the contents of the ontology to detect the healthcare record of a patient, and systematically provides to healthcare professionals the clinical information relevant to managing the patient. The second personalized process systematically transforms a healthcare description for general treatment into an individual interference plan. However, this system needs intelligent knowledge to present various healthcare descriptions for different conditions in the patient. Domain ontology and rules reasoning was proposed to construct a clinical decision support system for patients undergoing surgery [1]. This ontology has 31 classes, 13 properties, and 38 Apache Jena rules to generate a recommendation system for hospitalized diabetes patients. The system called GalemOWL was used to present ontology-based drug recommendation discovery [38]. This ontology demonstrated a semantic-enabled system that, together with standardized medical terminologies, provides a knowledge base for drug–drug and drug–disease interactions using rules and axioms. An ontological case–based engineering methodology was presented for diabetes management [39]. This case-based ontology, employed to support case semantic retrieval, improves case-based reasoning for understanding the input query and to retrieve the desired case. An actor-profile ontology was presented for organizational knowledge in home-care assistance [40]. The work proposed organizational knowledge for complex healthcare and customization of a home healthcare model designed by a European consortium of homecare professionals. An ontology-based healthcare recommendation system was presented to provide accurate information according to the user queries [41]. This system uses a semantic framework to analyze user's preference and recommend food and exercise. However, the continual increase of food information creates difficulty for ontology to extract precise information from the Internet. A semantic interoperability model for big-data in IoT (SIMB-IoT) was presented to recommend medicine for various symptoms collected from different sensors [42]. Two datasets are employed in the existing system. One dataset comprises medicines with side effects' information, and the second dataset contains the information of diseases with drug. Semantic annotations are used efficiently to transfer the information between patient and physician.

It is understood that type-1 fuzzy logic (T1FL) [43,44] and a classic ontology-based proposed system can monitor diabetes patients to some extent, and can classically provide health prescriptions. However, it cannot perfectly monitor when the risk factors of a patient increase and are intensively blurred. Besides, the IoT should be linked to semantic knowledge to automate the health prescription process for diabetes patients. Type-2 fuzzy logic (T2FL) with a fuzzy ontology is a solution to these problems. The three-dimensional structure of T2FL can easily handle vague data of risk factors [45,46], and a fuzzy ontology can represent decision knowledge to automate the overall health prescription system. An ontology was used to present the design of a diet assessment system [47]. In this study, fuzzy markup language was introduced to design type-2 fuzzy ontology–based knowledge for intelligent decision-making during food collection from the Internet and convenience stores. A T2FL and ontology model was proposed to personalize diabetes diet recommendations. This proposed approach retrieves meal records and a predefined food ontology to compile all kinds of foods for each person's diet goal. Type-2 fuzzy sets (T2FSs) were used to classify personal profiles and to categorize the calories in foods. However, these proposed ontologies are only concerned with an agent system to address diet goal–planning challenges by asking users to input eaten items and to exchange diet food information between users and domain experts.

In light of the above discussion on the existing systems, it is clear that there is a research gap in the area of chronic or diabetes patient monitoring and recommendations. Most of these systems are based on a classic ontology and type-1 fuzzy sets (T1FSs), which are unable to find patient health condition levels precisely and provide decision-making knowledge for food and drug recommendations. The classic ontology cannot achieve the desired instances when the patient's physiological information is intensively blurred. In addition, a T1FS-based system extracts data from uncertain features and the disease history of a chronic patient to a limited extent, and cannot perfectly address the recommendation problem. Therefore, the proposed T2FL and fuzzy semantic knowledge–based chronic-patient monitoring is a novel effort to design an automatic recommendation process for IoT-based healthcare.

## 3. Type-2 fuzzy logic-based patient health condition declaration

In this Section, the basic concepts of type-2 fuzzy logic-based health condition declaration are given. Lofti Zadeh introduced the type-1 fuzzy set in 1965 to extract vague and blurred concepts [48]. Zadeh extended the T1FS to the type-2 fuzzy set after 10 years [49]. A T2FS characterized by membership function (MF) $\mu_{\widetilde{A}}(x, \mu)$, where $x \in X$, $\mu \in J_x \subseteq [0, 1]$, is expressed as follows [50,51]:

$$\widetilde{A} = \{((x, \mu), \mu_{\widetilde{A}}(x, \mu)) \mid \forall x \in X \ \ \forall \mu \in J_x \subseteq [0, 1]\} \tag{1}$$

can also be expressed as

$$\widetilde{A} = \int_{x \in X} \int_{\mu \in J_x} \mu_{\widetilde{A}}(x, \mu)/(x, \mu) \ J_x \subseteq [0, 1] \text{ where } 0 \le \mu_{\widetilde{A}}(x, \mu) \le 1 \tag{2}$$

where $\int\int$ shows the union of overall admissible $x$ and $\mu$. $J_x$ is called the primary membership of x. There is a secondary membership value for each primary membership value. From Eqs. (1) and (2), $J_x \subseteq [0, 1]$ is a limitation that is equal to $0 \le \mu_{\widetilde{A}}(x, \mu) \le 1$ for type-1 membership functions (T1MFs), and $J_x$ indicates primary membership of $\widetilde{A}$, where $J_x \subseteq [0, 1]$ for $x \in X$. If $x = x'$ then, for each value of $x$, we have the following [52]:

$$\mu_{\widetilde{A}}(x') = \sum \mu \in J_{x'} f x'(\mu)/\mu, \text{ for } \mu \in J_{x'} \subseteq [0, 1] \text{ and } x' \in x \tag{3}$$

$$\text{FOU}(\widetilde{A}) = \bigcup_{\forall x \in X} J_{x'} = \{(x, \mu): \mu \in J_{x'} \subseteq [0, 1]\} \tag{4}$$

In Eqs. (3) and (4), $J_{x'}$ and $\mu_{\widetilde{A}}(x')$ are the primary membership and secondary membership function of $x'$, respectively. The T2FS contains two T1FS membership functions that bound FOU($\widetilde{A}$): a lower membership function (LMF) denoted by $\underline{\mu_{\widetilde{A}}}(x) \mid \forall x \in X$ and an upper membership function (UMF) denoted by $\overline{\mu_{\widetilde{A}}}(x) \mid \forall x \in X$, where

$$\overline{\mu_{\widetilde{A}}}(x) \equiv \overline{\mathrm{FOU}(\widetilde{A})}|\ \forall x \in X \tag{5}$$

and

$$\underline{\mu_{\widetilde{A}}}(x) \equiv \underline{\mathrm{FOU}(\widetilde{A})}|\ \forall x \in X \tag{6}$$

For interval of T2FS,

$$J_x = [\underline{\mu_{\widetilde{A}}}(x), \overline{\mu_{\widetilde{A}}}(x)],\ \forall x \in X \tag{7}$$

Let us consider the patient health condition that is defined by fuzzy sets. These fuzzy sets include blood pressure (Very Low, Low, Medium, High, Very High), blood sugar (Very Low, Low, Medium, High, and Very High), cholesterol (Very Low, Low, Medium, High, and Very High), movement speed of the body (Very Low, Low, Medium, High, and Very High), heart rate (Low, Medium, and High), age (Very Young, Young, Mild, Old, and Very Old), and weight (Light, Normal, and Heavy). These variables have uncertainty and cannot determine the membership degree as a classical number [0, 1]. In addition, this system is unable to provide efficient results using T1FS, because the type-1 membership functions (MFs) cannot fully represent the uncertainty of these fuzzy variables. Therefore, a T2FS is employed. The membership degree of a T2FS element is a fuzzy set in [0, 1], unlike a T1FS, where the membership degree is a crisp value, as shown in Fig. 1. The interval of type-2 fuzzy MFs (T2FMFs) is created by two type-1 fuzzy sets, as shown in Fig. 2. Fig. 2 shows that the interval of fuzzy membership values ranges from 0.4 to 0.6. The shaded region is called the footprint of uncertainty (FOU), which is the aggregation of all the primary MFs [51]. The UMF and LMF are fully enclosed by the shaded region. It shows the maximum and minimum values of $\mu$ for each $x$. In this paper, a triangular MF is used, which is described by four linear functions and five points (a, b, c, d, and e), as shown in Eqs. (8)–(10). The centroid of the T2FMF is calculated as the centroid of a T1FMF. These centroids are defined in Eqs. (11) and (12) [52]:

$$\mathrm{Triangular}(x,\ a,\ b,\ c,\ d,\ e) = \max(0,\ \min(z_1,\ z_2,\ e)) \tag{8}$$

$$z_1(x,\ a,\ b,\ c) = e\frac{x - e}{b - a} \tag{9}$$

$$z_2(x,\ c,\ d,\ e) = e\frac{d - x}{d - c} \tag{10}$$

$$c = \frac{\sum_{i=1}^{q} \mu\ (x_i).\ x_i}{\sum_{i=1}^{q} \mu\ (x_i)} \tag{11}$$

$$[c_l,\ c_r] = \left[\frac{\sum_{i=1}^{q} \mu^*\ (x_i).\ x_i}{\sum_{i=1}^{q} \mu^*\ (x_i)},\ \frac{\sum_{i=1}^{q} \mu^{**}\ (x_i).\ x_i}{\sum_{i=1}^{q} \mu^{**}\ (x_i)}\right] \tag{12}$$

where $\mu^{**}\ (x_i)$ and $\mu^*\ (x_i)$ are the values of the LMF and the UMF, which maximize and minimize the weighted average [50]. UMF = Triangular (x, 40, 75, 75, 140, 140) and LMF = Triangular (x, 60, 75, 75, 90, 90), as shown in Fig. 1. The intervals of the T2FMF for a fuzzy set $x_i$ are: $I_1$ = [0.2, 0.5] at $x_1$ = 63 and $I_2$ = [0.4, 0.6] at $x_2$ = 85.

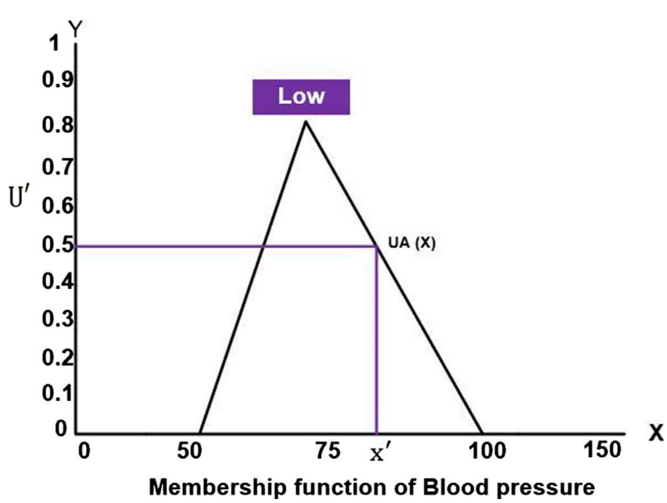


**Fig. 1.** Type-1 fuzzy set.

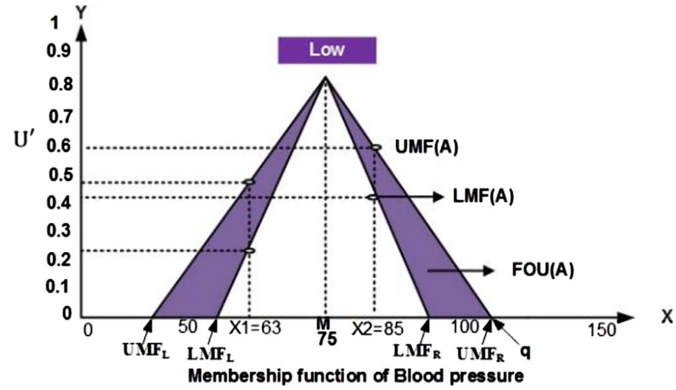


**Fig. 2.** Type-2 fuzzy set.

In general, Type-2 fuzzy control system consists of five components. Those are fuzzification, a type-2 fuzzy rule base, an inference engine, a type-reducer, and defuzzification. Fuzzification maps crisp inputs into the T2FS. The type-2 fuzzy rule base has "If-Then" rules (the same as a T1FS), but its antecedents and consequents are characterized by the T2FS. The inference engine allocates T2FS inputs to T2FS outputs employing the rules of a fuzzy rule base and operators (union and intersection). The type-reducer converts the T2F output sets to T1F output sets. Defuzzification further converts the T1FS into a crisp value, which is the average of right end points and left end points of the type-reduced set.

## 4. The design architecture of the proposed system

In this section, we illustrate the proposed healthcare monitoring and recommendation system with the help of a functional diagram that can be considered as the internal workflow of the proposed architecture. In the IoT, the health prescription process for chronic patients (patients who deserve long-term treatment and assistance) needs the data simultaneously in order to evaluate the patient's health condition [7,53]. These data are managed through decision-making knowledge provided by physicians. This decision-making knowledge includes instructions to evaluate the test results and to measure patient frequencies through sensors. These test results and frequency measurements are intelligently classified using type-2 fuzzy logic to describe the patient's health condition. Decision-making knowledge also includes instructions to recommend medicines and foods. It is connected to a smart medicine box and a smart refrigerator to effectively recommend drugs and foods according to the patient's health condition. All this information includes the patient's, nurses', and physicians' personal data, evaluation of test results, physicians' instructions, T2FL-based classifications, and drug and food recommendations designed in an ontology to represent decision-making knowledge (as a health prescription system) for long-term care of chronic-disease patients. The architecture of this system is based on a security layer and a decision-making knowledge layer, as shown in Fig. 3. The security layer prevents unauthorized access to medical devices, and investigates the true condition of the right patient before assigning drugs and food. The patient ontology retrieves the patient's personal information (age, weight, height, sex, etc.) and disease history from the database. Different sensors collect physical data (cholesterol and blood sugar levels, blood pressure, heart rate, body motion, kidney function, electromyography (EMG), electrocardiogram (ECG) etc.) storing them in a sensor ontology. These data are also the input variables for fuzzification, which maps these variables into a type-2 fuzzy membership function (T2FMF) to make a set of intervals for T1Fs. The

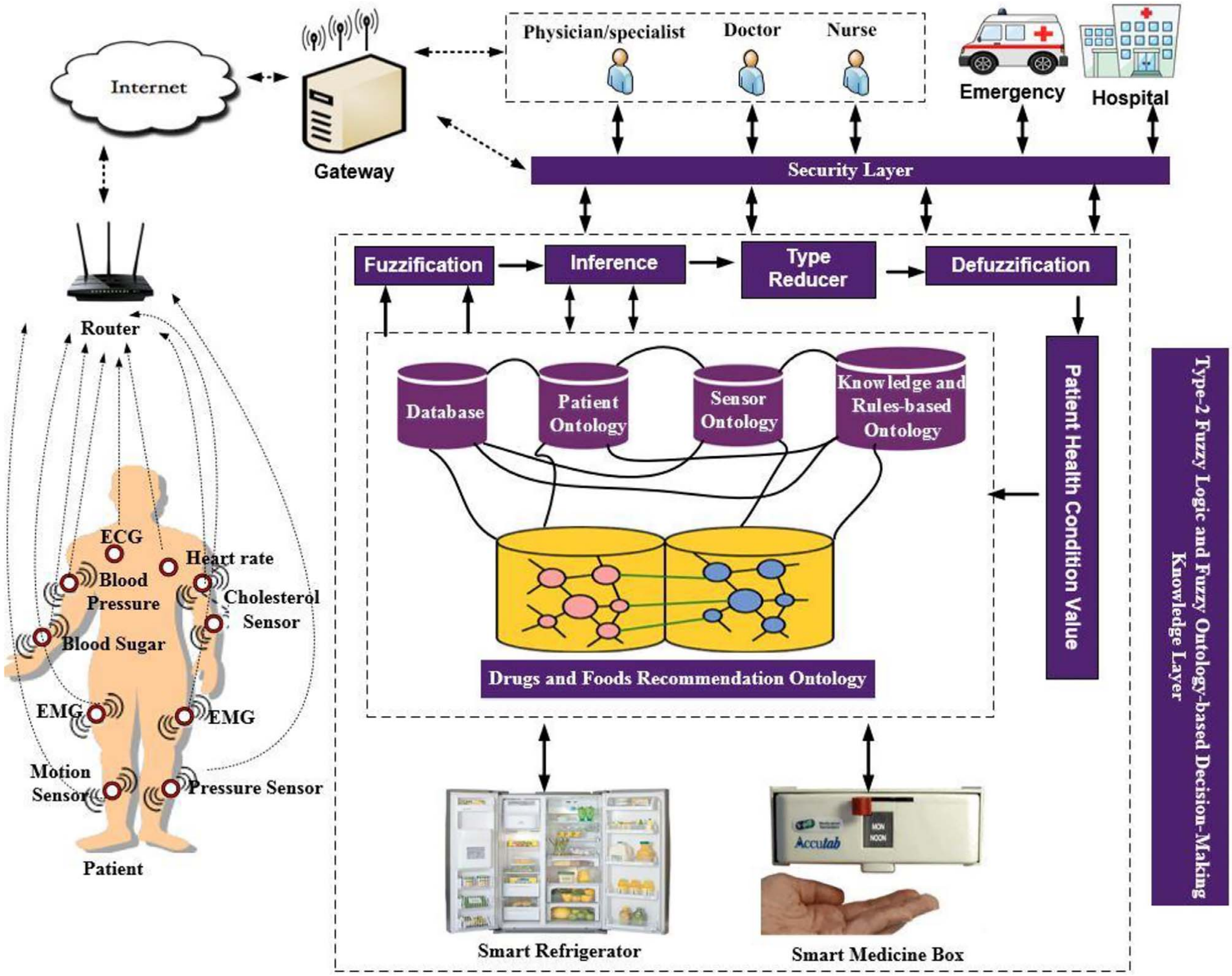


**Fig. 3.** Type-2 fuzzy logic and fuzzy ontology–based decision-making knowledge for health prescription architecture.

inference part assigns fuzzy input variables to fuzzy output variables using the rules in the rule base and operators, such as join ($^{\vee}$) and meet ($^{\wedge}$). The rules are described in the knowledge and rule–based ontology. The type reducer transforms the type-2 fuzzy output of the inference function for the T1FSs. Defuzzification calculates the average type reducer, which is the value of the patient health condition. This value is then assigned to the fuzzy ontology for further processing. In the ontologies, the data (output variables) are classified as Very Low (VL), Low (L), Medium (M), High (H), and Very High (VH) in order to recommend drugs and foods according to the patient's health condition. This system can handle any type of situation related to the diabetes health prescription domain. The drug and food recommendation ontology and the patient's personal ontology are executed offline and must be processed with a health prescription via the concepts of the fuzzy ontology. The recommendation ontology captures the information about diabetes medications, patient test results, and diabetes-friendly foods. Collection of data is a primary task and can help to speed up the construction process of this ontology. The diabetes drug and food information is gathered from the Internet and research articles, and classified manually under the supervision of domain experts [54]. Physicians regularly modify the recommendation ontologies, and the smart medicine box and smart refrigerator connect to these ontologies to provide drugs and foods. The next sections elaborate on the internal workings of the proposed system, one by one.

## 5. Type-2 fuzzy logic and fuzzy ontology–based decision-making knowledge layer

An ontology is used to arrange information and to share domain knowledge among systems and people. An ontology is written in a specific language called Web Ontology Language (OWL) [55]. Protégé OWL is open source software that is used to develop the proposed ontology. This software uses Java-based graphical applications to create and maintain classic and fuzzy ontologies. To achieve the efficiency of the proposed ontology, first, a classic ontology is developed, and then a semi-automatic plugin called Fuzzy OWL is employed to insert fuzzy terms into the classic ontology. DL and SPARQL queries are used to retrieve the needed information from the ontology. The proposed ontology contains classes, fuzzy data types, data properties, object properties, instances, and axioms, as shown in Fig. 4. These classes show the concepts of health prescription knowledge. Data and object properties define the relationships and attributes of the class connected to the basic data types. Fuzzy data type describes the intervals of the membership variable. For example, blood sugar has five membership variables: Blood-Sugar-Very-Low, Blood-Sugar-Low, Blood-Sugar-Medium, Blood-Sugar-High, and Blood-Sugar-Very-High. The interval of 'Blood-Sugar-High' can be defined as (double [> = 140.0] and double [< = 200.0]), while its fuzzy OWL trapezoidal representation is <fuzzyOwl2 fuzzy Type = "datatype"> <Datatype type = "trapezoidal" a = "140" b = "170" c = "170" d = "200" /> </fuzzyOwl2>. The relationships among these classes and instances are shown in Fig 5. In Fig. 5, the yellow circle, purple diamond, and colored lines represent

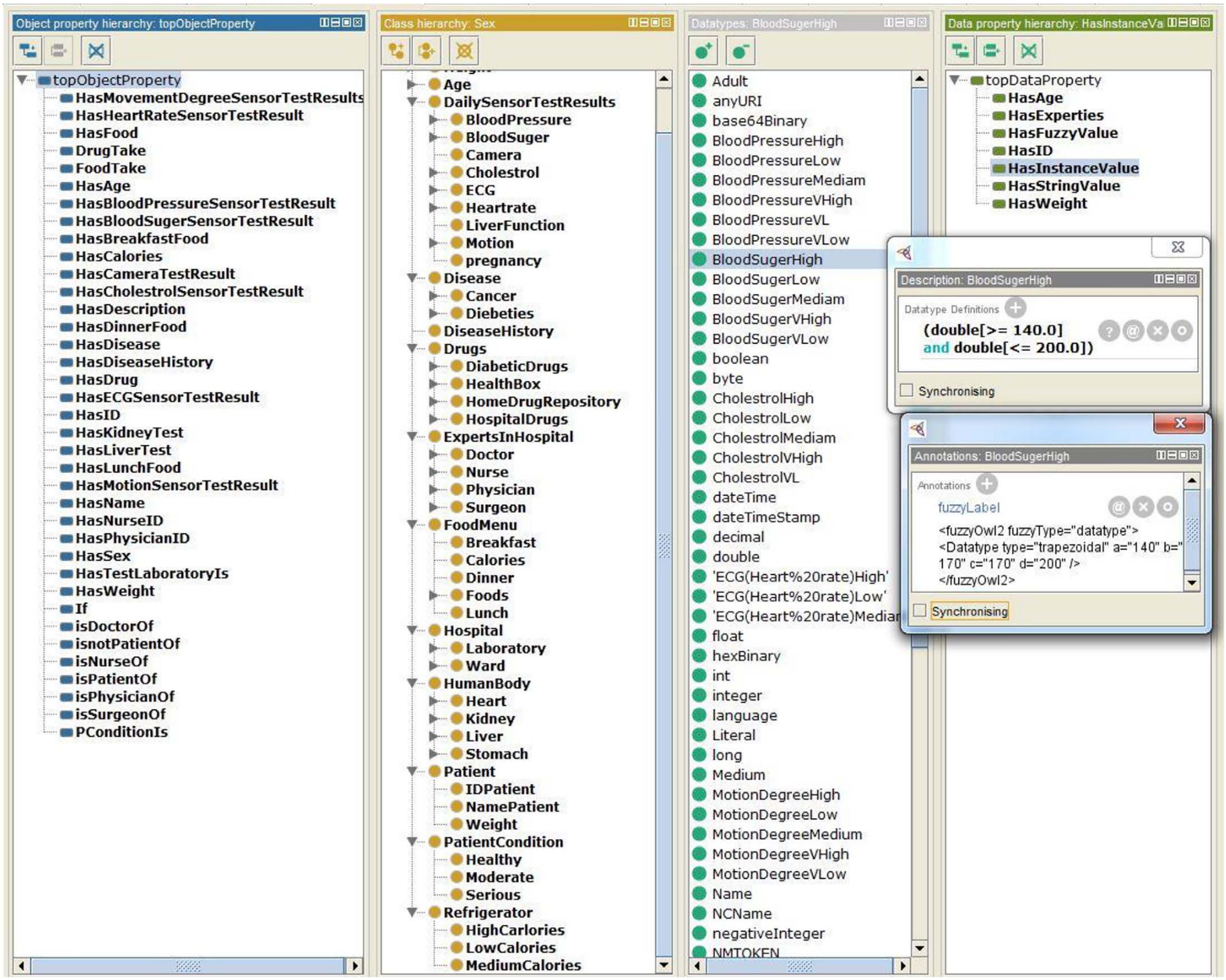


**Fig. 4.** Fuzzy ontology classes, objects, data properties, and fuzzy data types.

classes, instances, and the relationships among them, respectively. Each line color shows the data property, domain, and range among the classes and instances. All previous studies related to classic ontology–based health systems are limited to classifying vague information more efficiently. Therefore, this paper proposes fuzzy ontology–based semantic knowledge for intelligent decision-making during the computation of patient health condition values, as well as drug and food recommendations.

### 5.1. Fuzzy patient ontology

The history of a chronic patient is an important factor for decision-making by the physician. Therefore, all the information that could be required to supervise a chronic patient's condition is included in a classic patient ontology. This information includes patient personal data and disease history, which are easily acquired by physicians and patients. This classic patient ontology is a subsection of a fuzzy ontology, in which the membership degrees of all properties and relations are equal to 1. Most of the patient data are ambiguous; therefore, classic elements of a patient ontology are fuzzified using fuzzy data types and fuzzy modifiers [13]. The proposed patient ontology contains fuzzy concepts and relations to express vague knowledge for imprecise data. The fuzzy concept is a concept where the instance belongs to a certain degree. For example, 'heavy-patient' (weight) is a fuzzy concept, where 'heavy' is an ambiguous predicate; the concept is also ambiguous, and therefore, 'heavy' can be represented as a fuzzy concept, such as 'patient Goro is an instance heavy-patient at membership degree 0.8'. Object and data properties are fuzzy relations. An object relation connects instances at a membership degree and allows fuzzy role assertion, such as 'Goro has-blood-pressure-sensor-test-result BP-very-high at a degree 0.8'. The property 'has-blood-pressure-sensor-test-result' connects instances 'Goro' and 'BP-very-high'. Data type relations assign a literal value to instances or individuals at a certain degree; for example, 'patient Goro has age old at degree 0.7'. Here, 'has age' is a data property that connects instances 'Goro' and 'old'. The patient ontology contains five fuzzy variables: 'age', 'weight', 'sex', 'height' and 'disease history' in the concept of 'patient profile' [47]. The fuzzy variable 'age' has fuzzy sets 'young', 'adult', and 'old'. Similarly, a fuzzy variable 'weight' has the fuzzy sets 'light', 'normal', and 'heavy'. These fuzzy variables are important factors for a diabetes patient's supervision, which are described in patient ontology using fuzzy OWL.

### 5.2. Sensor ontology

A sensor ontology is a personalized solution for chronic patient monitoring. This ontology is linked to the patient ontology and the

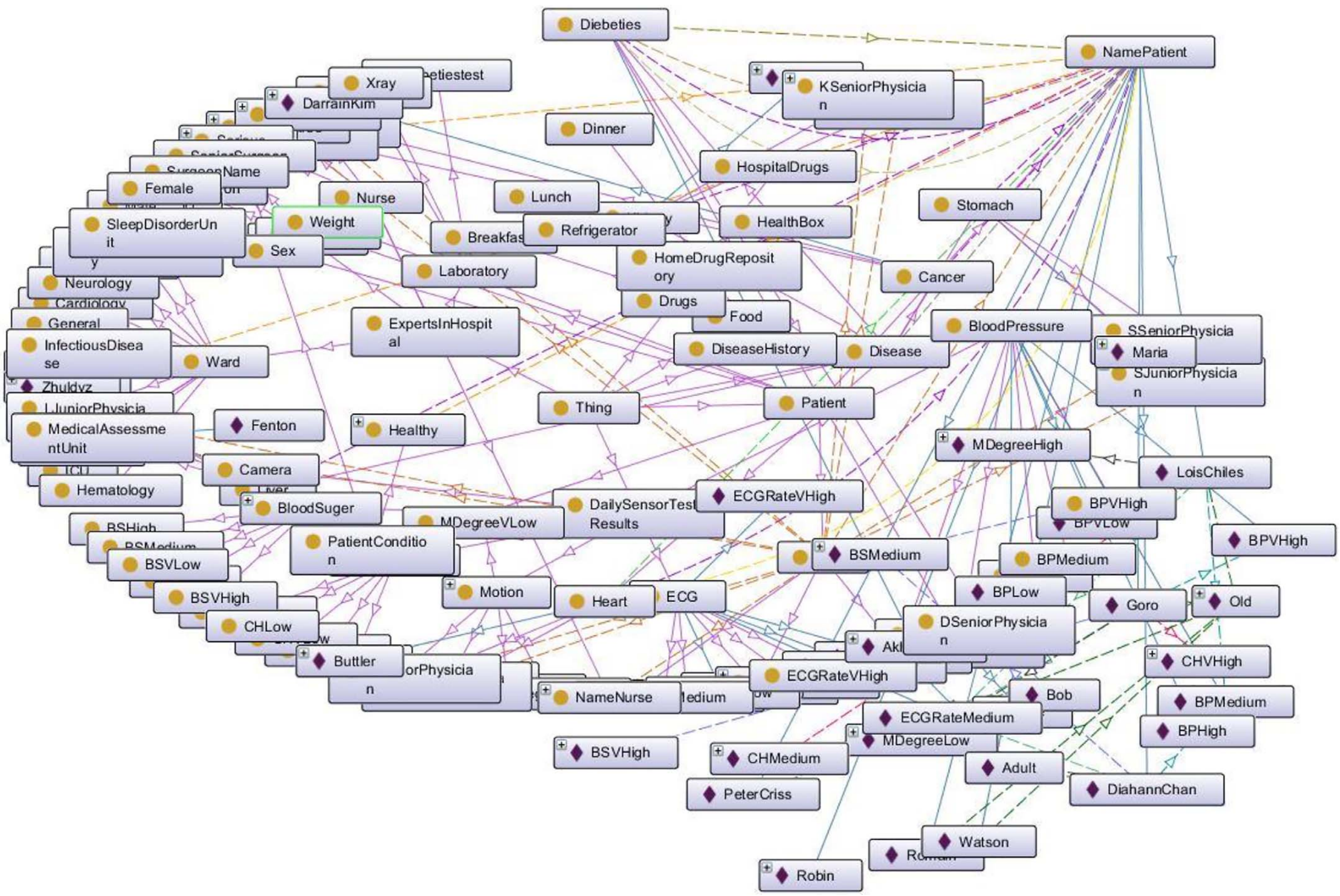


**Fig. 5.** Relationships among fuzzy ontology terms.

knowledge and rule–based ontology. Apart from instances (name, age, id, weight, etc.) of the patient ontology, different rules in the knowledge and rule–based ontology are defined for each sensor test. The main aim of this sensor ontology is to describe and mange those data that are needed for monitoring and task execution. There are two kinds of test for patient monitoring: questionnaires and body measurements. A lot of research has been done on questionnaires [14,15,56]. However, there are still limitations to intelligent semantic knowledge for body measurements in IoT-based health prescription systems. Therefore, body measurement using sensors and their instances in the ontology are configured in order to know about patient activities and health conditions. This ontology contains 8 measurement sensors as instances of the class daily-sensor-test-results. The class daily-sensor-test-results has subclasses, and every subclass has instances with the same name of the class. These instances are blood sugar, glycated hemoglobin (HBA1C), blood pressure, cholesterol, heart rate, motion, weight, and height. With every measurement, the physician needs a camera to retrieve patient information like the patient's position (sitting, walking, sleeping, or standing), for which arm is used for the blood pressure sensor, and for the types of foods the patient ate and drank in the previous hour. These sensors (as input variables) and the fuzzy linguistic data types and MFs are described as follows.

1. Blood pressure: The pressure exerted by circulating blood on the walls of blood vessels is called blood pressure [57]. There are three types of blood pressure: systolic, diastolic, and mean arterial pressure (MAP), which are described as subclasses of blood pressure in the ontology. In our proposed system, systolic pressure is used for measurement. There are five fuzzy sets of blood pressure. These fuzzy sets with OWL data–range expressions are as follows: Very-Low (double [> = 0.0] and double [< = 90.0]), Low (double [> = 71.0] and double [< = 130.0]), Medium (double [> = 125.0] and double [< = 154.0]), High (double [> = 142.0] and double [< = 180.0]), and Very-High (double [> = 165.0] and double [< = 250.0]).
2. Blood sugar: Blood sugar, or blood glucose, supplies energy to all cells of the body. However, it is very important to keep it in a normal range. There are two ways to measure blood sugar: millimoles per liter (mmol/L) and milligrams per deciliter (mg/dL). This system uses milligrams per deciliter. The ontology contains five fuzzy sets for blood sugar. These fuzzy sets with fuzzy OWL data expressions are as follows: Very-Low (double [> = 0.0] and double [< = 45.0]), Low (double [> = 30.0] and double [< = 90.0]), Medium (double [> = 75.0] and double [< = 160.0]), High (double [> = 140.0] and double [< = 200.0]), and Very-High (double [> = 180.0] and double [< = 300.0]).
3. Cholesterol: Cholesterol is produced from food and the body. The physician always determines the chronic patient's cholesterol level before prescribing medication, because it predicts the patient's risk of heart disease [23]. There are two kinds of cholesterol, high-density lipoprotein (HDL), or "good" cholesterol, and low-density lipoprotein (LDL) or "bad" cholesterol. This system considers the LDL cholesterol level. The cholesterol fuzzy sets with ranges are as follows. Very-Low (double [> = 0.0] and double [< = 170.0]), Low (double [> = 150.0] and double [< = 200.0]), Medium (double [> = 180.0] and double [< = 250.0]), High (double [> = 225.0] and double [< = 315.0]), and Very-High (double [> = 280.0] and double [< = 400.0]).
4. Movement speed of the body: This input variable is used to find movement speed of an old patient's body. There are four types for

range of motion (ROM), which can be used to examine the patient's body movement: passive ROM, active-assisted ROM, active ROM, and active self–assisted ROM [58]. In this proposed system, active ROM (movement by the patient alone) is described to find the movement degree of the patient's body. There are five fuzzy linguistic sets for body movement. These sets, along with their ranges, are as follows: Very-Low (double [> = 0.0] and double [< = 10.0]), Low (double [> = 8.0] and double [< = 30.0]), Medium (double [> = 25.0] and double [< = 40.0]), High (double [> = 35.0] and double [< = 50.0]), and Very-High (double [> = 45.0] and double [< = 70.0]).

5. Heart rate: It has been confirmed that daily heart rate analysis of diabetes patients is important for detecting and treating heart disease in its early stages [23]. Therefore, this system uses three fuzzy variables for heart rate to compute the patient's health condition. These fuzzy sets, along with ranges, are as follows. Low (double [> = 30] and double [< = 60.0]), Medium (double [> = 50.0] and double [< = 100.0]) and High (double [> = 95.0] and double [ < = 120.0].
6. Age: This input variable is divided into five linguistic asset value variables (Very Young, Young, Mild, Old, Very Old). These linguistic variables, along with their ranges, are as follows: Very Young (double [> = 0.0] and double [< = 20.0]), Young (double [> = 16.0] and double [< = 38.0]), Mild (double [> = 35.0] and double [< = 50.0], Old (double [> = 45.0] and double [ < = 60.0] and Very Old (double [> = 55.0] and double [< = 65.0].
7. Weight: This input variable has three fuzzy sets (Light, Normal, and Heavy). The ranges of these variables in the ontology are: Light (double [> = 0.0] and double [< = 45.0]), Normal (double [> = 35.0] and double [< = 75.0]) and Heavy (double [> = 95.0] and double [< = 140.0].
8. Sex and Height: The variable sex is crisp and contains two values (0 and 1). Therefore, two subclasses of 'sex' along with instances (male and female) are described in the ontology. If the patient is male, then the value is 0, and if the patient is female, then 1 is assigned during computation of the patient condition. Height is also an important factor for diabetes patient treatment, because other variables, like weight, depend on it. However, very limited changes occur in patient height; therefore, it is described in the ontology for food recommendations, and is not considered during the patient condition value computation.
9. Patient health condition: This output variable defines the patient health condition. It is dependent on the type-2 fuzzy inference mechanism of the above-mentioned input variables. The fuzzy sets of this output variable are Healthy, Moderate, and Serious, and their ranges are: Healthy (double [> = 0.0] and double [< = 5.0]), Moderate (double [> = 2.5] and double [< = 7.5.0]), and Serious (double [> = 5.0] and double [< = 10.0]. The proposed system helps the medical staff by automatically informing them about the patient's health condition; for example, if the patient condition value is in range 0 ~ 5, the system shows that the patient condition is healthy. If the value is in range of 2.5 ~ 7.5, the system informs the medical staff to start regular services, and it automatically recommends drugs and foods for the patient using decision-making knowledge from the fuzzy ontology. If the patient condition value is in the range 5 ~ 10, the system indicates that the patient's condition is serious, calls emergency services or rescue units, and spontaneously changes food and drug recommendations. The MFs of this output variable are shown in Fig. 6(h). The type-1 fuzzy sets are shown as a thin line, whereas the interval type-2 fuzzy sets are shown as a thick line.

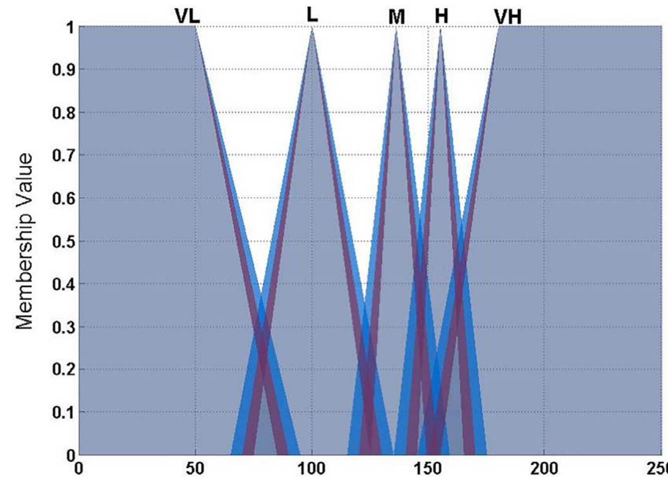


**Fig. 6. a.** MFs of blood pressure. **b**. MFs of blood sugar. **c**. MFs of cholesterol. **d.** MFs for movement speed of the body. **e.** MFs of heart rate. **f.** MFs of age. **g**. MFs of weight. **h**. MFs of health condition.

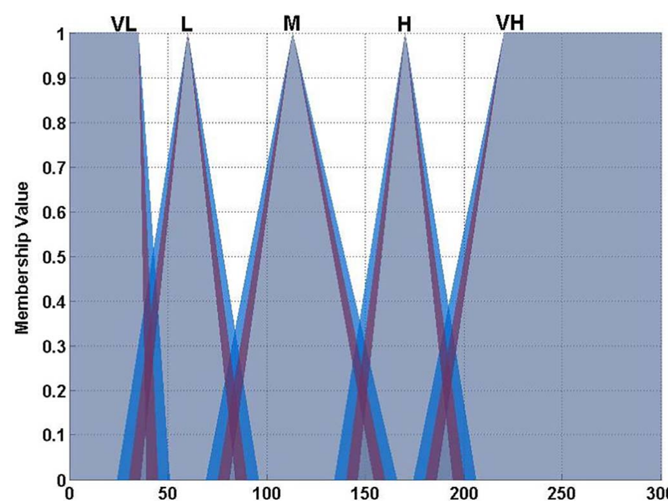


**Fig. 6.** (*continued*)

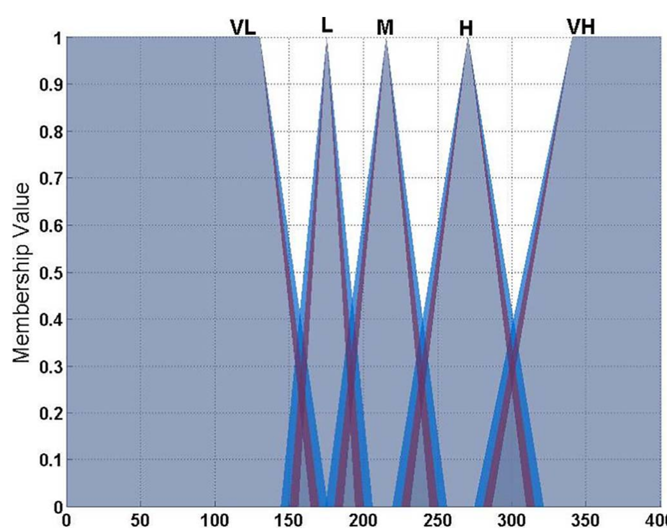


**Fig. 6.** (*continued*)

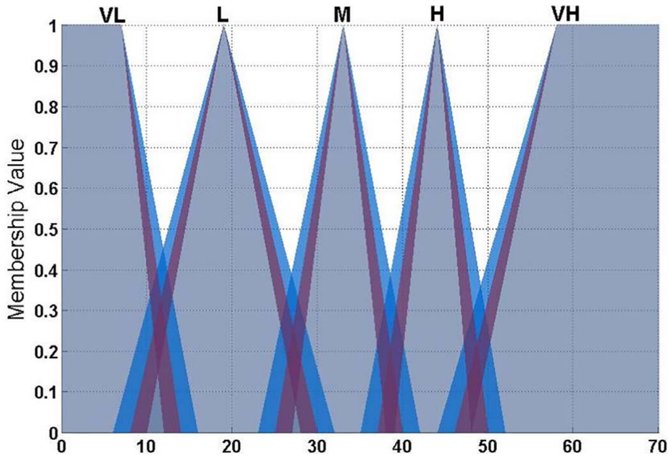


**Fig. 6.** (*continued*)

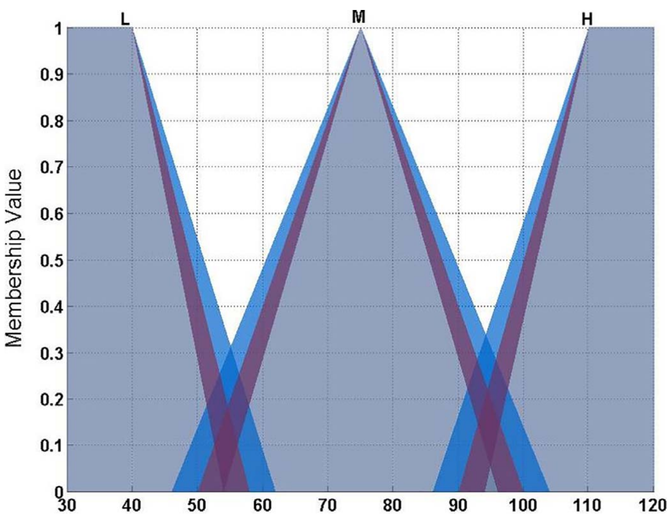


**Fig. 6.** (*continued*)

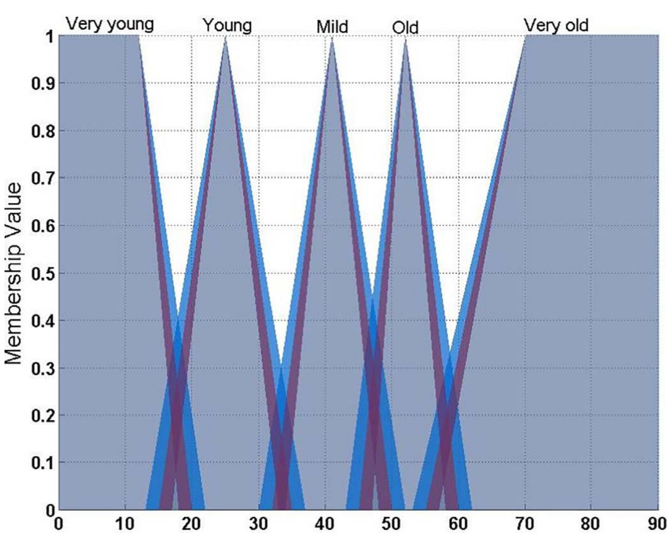


**Fig. 6.** (*continued*)

### *5.3. Patient health condition value computation based on type-2 fuzzy inference layer*

A type-2 fuzzy inference layer contains five parts. Those are fuzzification, a type-2 fuzzy rule base and inference engine, type reducer,

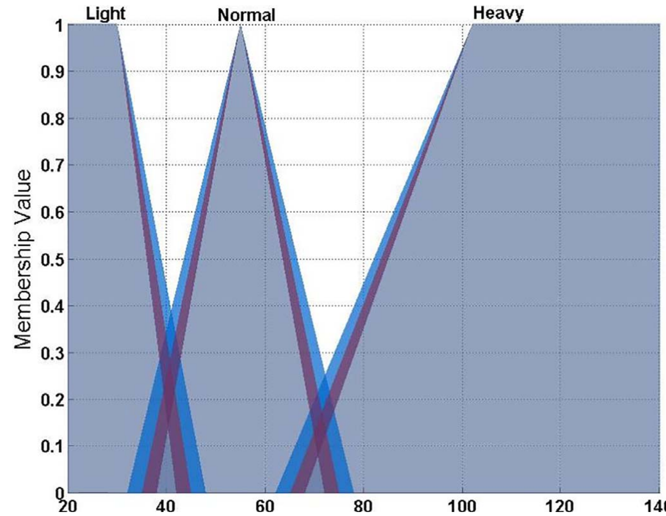


**Fig. 6.** (*continued*)

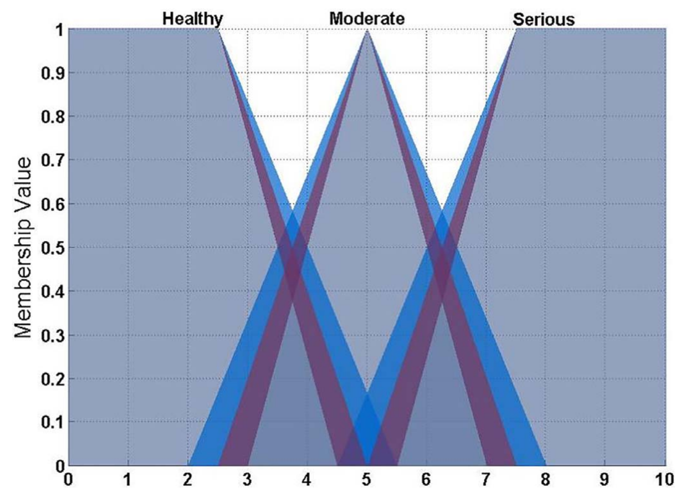


**Fig. 6.** (*continued*)

and defuzzification. At first, the crisp input values of sensors are converted to fuzzy input values using different MFs known as fuzzification. The inference mechanism is applied to make a set of rules, which can convert the fuzzy output into single set. The type reducer converts the output of inference mechanism to T1FSs, and then the defuzzification converts the type reduced sets back to crisp value as shown in Fig. 7.

#### *5.3.1. Fuzzification*

The sensors data are fuzzified using various triangular MFs, as explained in Section 5.2. The fuzzy sets of fuzzy variables (sensors) and T2FSs parameters have been defined in Table 1. The designed MFs for each input variable of blood pressure, blood sugar, cholesterol, movement speed of the body, heart rate, age, weight, and patient health condition are shown in Fig. 6(a)–(h), respectively. In previous research, the MFs of FOU are considered with equal span and width, which may not provide best results. In this paper, the MFs are selected based on previous studies and different results. The fuzzification takes the sensors data and maps it into an interval of T2FMFs to create a T1Fs intervals.

#### *5.3.2. A type-2 fuzzy rule base and inference engine*

The core of this proposed system is T2FSs and fuzzy ontology–based decision-making knowledge, which not only provides the knowledge and rules to compute the patient health condition value but also assists the medical staff (nurses and doctors) to retrieve the patient's needed

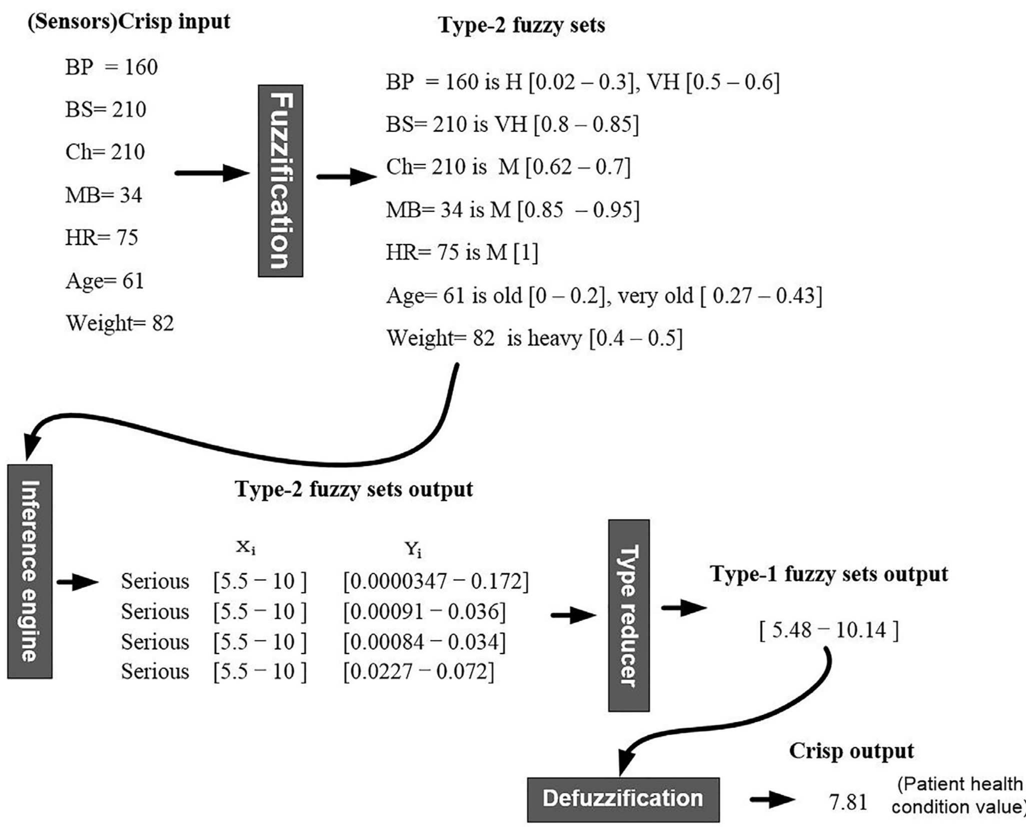


**Fig. 7.** Computation of patient health condition value.

information using SPARQL and DL queries [59,60]. Knowledge and rules are the core of the type-2 fuzzy inference system. Researchers have used it in different fields, such as opinion mining, robotics, collision avoidance, expert systems, etc. [61,62]. Due to the efficiency in a variety of fields, the knowledge and rule–based system is also known by other names, such as fuzzy associative memory, fuzzy expert system, fuzzy modeling, and fuzzy controller. Examining the knowledge and rule–based system, it is divided into three parts: knowledge (the database), the rule base, and the reasoning mechanism. The knowledge aspect shows the fuzzy variables, fuzzy concepts, fuzzy terms, and fuzzy set membership functions, as explained in the previous sections, whereas the rule base explains the fuzzy rules, such as antecedent and consequent rules. In our ontology, the "SWRLTab" Semantic Web Rule Language plugin of Protégé edits the rules, as shown in Fig. 8. This plugin allows users to enter the rules for any sort of ontology-based system. There are different input variables (blood sugar, blood pressure, cholesterol, heart rate, movement speed, weight, height, and temperature), one output variable (patient health condition), and various rules like *(isDoctorOf(?Z, ?Y), isPatientOf(?X, ?Y) -> isPhysicianOf(?Z, ?X))* in the knowledge and rule–based ontology. The fuzzy decision extracts these rules, finds the patient health condition, and then assigns this value to an ontology instance. This instance describes the patient health condition in the ontology for the purposes of drug and food recommendations. This layer contains five components, the fuzzification, inference, type-reducer, defuzzification and knowledge and rule–based fuzzy ontology. After fuzzification, the inference aspect applies the rules to the fuzzy interval membership function. The rules and intervals with linguistic values are stored in the knowledge and rule–based ontology. All these rules can be expressed as follows:

Rule$_1$: IF $A_1$ is $x_1$ AND $B_1$ is $y_1$ THEN $C_1$ is $z_1$
Rule$_2$: IF $A_2$ is $x_2$ AND $B_2$ is $y_2$ THEN $C_2$ is $z_2$
Rule$_3$: IF $A_3$ is $x_3$ AND $B_3$ is $y_3$ THEN $C_3$ is $z_3$
… …………..
Rule$_n$: IF $A_n$ is $x_n$ AND $B_n$ is $y_n$ THEN $C_n$ is $z_n$

where $A_1$ and $B_1$ are the input variables, $C_1$ is the output and control variable, and x, y, and z are linguistic values for the linguistic variables A, B, and C, respectively. The proposed ontology has various inputs and one output fuzzy variable, which can be expressed by 69 rules. Some rules, as follows, are described so that readers can understand the utilization of all rules.

Rule$_1$: Patient(?X), Disease(?Y), Physician(?Z), isPatient Of(?X, ?Y), isPhysicianOf(?Z, ?Y) -> isPhysician Of(?Z, ?X)

Explanation of Rule 1: If X is a patient of heart and Z is a physician of cardiology (heart), then Z is a physician of X. For example, this rule is applied when the patient heart rate is irregular; the system triggers an alert to the cardiologist for immediate care of the patient.

Rule$_2$: Patient(?X), HasBloodPressureSensorTestResult(?X, BPHigh), HasBloodSugarSensorTestResult(?X, BSVHigh), HasCholesterol SensorTestResult(?X, CHVHigh), HasHeartRateSensorTestResult(?X, HRHigh), greaterThan(?BPHigh, 142), greaterThan(?BSVHigh, 200), greaterThan(?CHVHigh, 280), greaterThan(?HRHigh, 95), lessThan (?BPHigh, 180), lessThan(?CHVHigh, 500), lessThan(?HRHigh, 120) -> PConditionIs(?X, Serious), isPhysicianOf(?A, ?X)

Explanation of Rule 2: If the blood pressureOf of patient X is between 142 and 180, blood sugar is greater than 200, cholesterol is between 280 and 500, and the heart rate is between 95 and 120; then the patient condition is serious, and the physicianOf A (each disease) should be alerted to immediately care for patient X.

Rule$_3$: Patient(?X), HasMovementDegreeSensorTestResults(?X, MDegreeLow), greaterThan(?MDegreeLow, 0), lessThan (?MDegreeLow, 10) -> PConditionIs(?X, Serious), isNurseOf(?Y, ?X)

Explanation of Rule 3: If the movement rangeOf patient X is between 0 and 10, then the patient condition is serious, and nurse Y should be selected to help and take careOf patient X.

Rule$_4$: Patient(?X), HasBloodPressureSensorTestResult(?X, BPVHigh), HasBloodSugarSensorTestResult(?X, BSVHigh), HasChol esterolSensorTestResult(?X, CHVHigh), HasHeartRateSensorTestResult (?X, HRMedium), greaterThan(?BPVHigh, 165), lessThan(?BPVHigh,

**Table 1**
Parameters of the type-2 fuzzy set.

| Fuzzy variable | Linguistic term | {[$\mathrm{LMF_L}$, $\mathrm{M_{LMF_L}}$, $\mathrm{M_{LMF_R}}$, $\mathrm{LMF_R}$], [$\mathrm{UMF_L}$, $\mathrm{M_{UMF_L}}$, $\mathrm{M_{UMF_R}}$, $\mathrm{UMF_R}$]} |
|---|---|---|
| Blood pressure | VL | {[0, 0, 50, 90], [0, 0, 50, 110]} |
| | L | {[75, 100, 100, 125], [65, 100, 100, 140]} |
| | M | {[125, 135, 135, 150], [117, 135, 135, 158]} |
| | H | {[145, 160, 160, 172], [140, 160, 160, 180]} |
| | VH | {[155, 175, 250, 250], [145, 175, 250, 250]} |
| Blood sugar | VL | {[0, 0, 35, 45], [0, 0, 35, 55]} |
| | L | {[35, 75, 75, 90], [25, 75, 75, 100]} |
| | M | {[80, 120, 120, 155], [75, 120, 120, 165]} |
| | H | {[147, 175, 175, 198], [140, 175, 175, 205]} |
| | VH | {[190, 220, 300, 300], [180, 220, 300, 300]} |
| Cholesterol | VL | {[0, 0, 130, 160], [0, 0, 130, 175]} |
| | L | {[155, 175, 175, 190], [145, 175, 175, 205]} |
| | M | {[180, 220, 220, 240], [175, 220, 220, 255]} |
| | H | {[230, 270, 270, 315], [220, 270, 270, 325]} |
| | VH | {[285, 340, 400, 400], [270, 340, 400, 400]} |
| Movement speed of the body | VL | {[0, 0, 8, 12], [0, 0, 8, 17]} |
| | L | {[10, 18, 18, 28], [6, 18, 18, 32]} |
| | M | {[27, 33, 33, 38], [24, 33, 33, 43]} |
| | H | {[40, 44, 44, 48], [35, 44, 44, 53]} |
| | VH | {[49, 58, 70, 70], [45, 58, 70, 70]} |
| Heart rate | L | {[30, 30, 40, 54], [30, 30, 40, 62]} |
| | M | {[55, 75, 75, 96], [46, 75, 75, 104]} |
| | H | {[95, 110, 120, 120], [86, 110, 120, 120]} |
| Age | Very young | {[0, 0, 12, 18], [0, 0, 12, 20]} |
| | Young | {[17, 25, 25, 33], [14, 25, 25, 36]} |
| | Mild | {[34, 41, 41, 48], [30, 41, 41, 52]} |
| | Old | {[46, 52, 52, 58], [44, 52, 52, 63]} |
| | Very old | {[58, 70, 90, 90], [54, 70, 90, 90]} |
| weight | Light | {[20, 20, 30, 42], [20, 20, 30, 52]} |
| | Normal | {[38, 53, 53, 72], [32, 53, 53, 78]} |
| | Heavy | {[68, 102, 140, 140], [62, 102, 140, 140]} |
| Patient health condition | Healthy | {[0, 0, 2.5, 4.5], [0, 0, 2.5, 5.5]} |
| | Moderate | {[3, 5, 5, 7], [2, 5, 5, 8]} |
| | Serious | {[5.5, 7.5, 10, 10], [4.5, 7.5, 10, 10]} |

250), greaterThan(?BSVHigh, 200), greaterThan(?CHVHigh, 280), lessThan(?CHVHigh, 500), greaterThan(?HRMedium, 50), lessThan (?HRMedium, 100) -> PConditionIs(?X, Serious), isPhysicianOf(?A, ?X)

Explanation of Rule 4: If the blood pressure Of patient X is between 165 and 250, blood sugar is greater than 200, cholesterol is between 280 and 500, and the heart rate is between 50 and 100; then the patient condition is serious, and the physician for A (each disease) should be alerted to immediately care for patient X.

Rule$_5$: Patient(?X), HasBloodPressureSensorTestResult(?X, BPLow), HasBloodSugarSensorTestResult(?X, BSMedium), HasCholesterol SensorTestResult(?X, CHVLow), greaterThan(?BPLow, 71), lessThan (?BPLow, 130), greaterThan(?BSMedium, 75), lessThan(?BSMedium, 160), greaterThan(?CHVLow, 0), lessThan(?CHVLow, 170) -> PConditionIs(?X, Moderate), isPhysicianOf(?A, ?X)

Explanation of Rule 5: If the blood pressure Of patient X is between 71 and 130, blood sugar is between 75 and 160, and cholesterol is between 0 and 170; then patient X's condition is moderate, and the medical staff is called to administer medicati°n.

Rule$_6$: Patient(?X), HasBloodPressureSensorTestResult(?X, BPVL ow), HasBloodSugarSensorTestResult(?X, BSMedium), HasCho lesterolSensorTestResult(?X, CHVLow), greaterThan(?BPVLow, 0), lessThan(?BPVLow, 90), greaterThan(?BSMedium, 75), lessThan (?BSMedium, 160), greaterThan(?CHVLow, 0), lessThan(?CHVLow, 170) -> PConditionIs(?X, Moderate), isPhysicianOf(?A, ?X)

Explanation of Rule 6: If the blood pressure Of patient X is between 0 and 90, blood sugar is between 75 and 160 and cholesterol is between 0 and 170; then the patient condition is moderate, and the physician Of A (each disease) should administer medication.

Rule$_7$: Patient(?X), HasBloodPressureSensorTestResult(?X, BPMedium), HasBloodSugarSensorTestResult(?X, BSMedium), HasCholesterolSensorTestResult(?X, CHVLow), greaterThan (?BPMedium, 125), lessThan(?BPMedium, 154), greaterThan (?BSMedium, 75), lessThan(?BSMedium, 160), greaterThan(?CHVLow, 0), lessThan(?CHVLow, 170) -> PConditionIs(?X, Healthy)

Explanation of Rule 7: If the blood pressure Of patient X is between 125 and 154, blood sugar is between 75 and 160, and cholesterol is between 0 and 170; then the patient condition is healthy.

Rule$_8$: Patient(?X), HasBloodPressureSensorTestResult(?X, BPHigh), greaterThan(?BPHigh,142), lessThan(?BPHigh, 180) -> HasDrug(?X, HighDrugs), HasFood(?X,HighDiabetic)

Explanation of Rule 8: If the blood pressure Of patient X is between 142 and 180, then the system should advise on high-level diabetes medication and foods.

### 5.3.3. Type reducer and defuzzification

After extracting the membership values and rules, the inference engine assigns the T2F interval outputs to the type-reducer. The type-reducer converts the T2F outputs to the T1FMF by using the Karnik–Mendel Algorithm (KMA), which is based on the calculation of the centroid, as explained in Eqs. (11) and (12). The defuzzifier

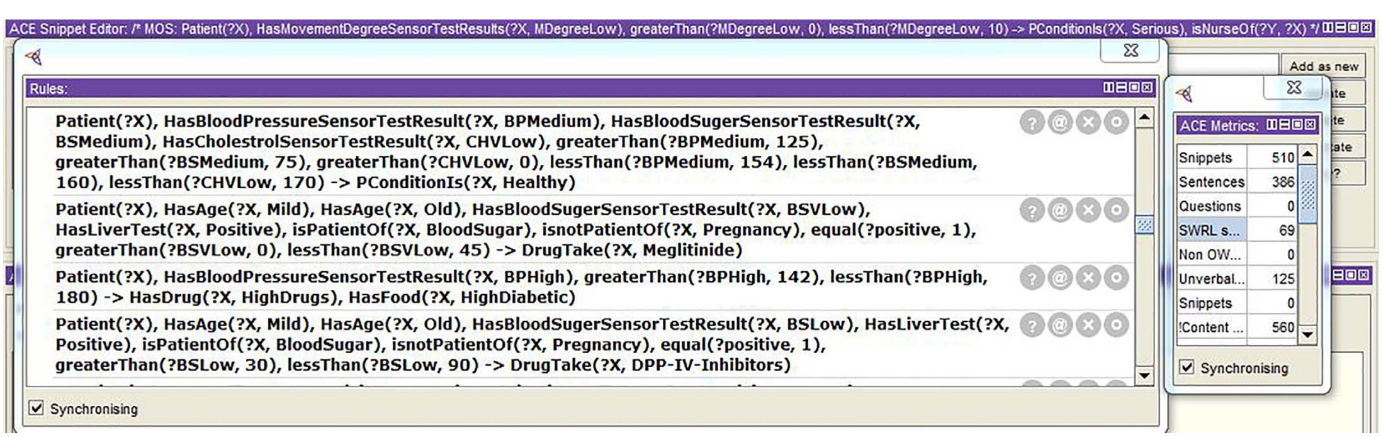


**Fig. 8.** Rules after Fact+ + + + reasoner execution.

calculates the average of the type-reducer left and right points to provide the result in the form of a value, which is called the patient condition value.

### 5.4. Drugs and foods recommendation

The rules and tests for chronic patient monitoring are explained in Sections 5.2 and 5.3. However, diabetes (blood sugar) drugs are only considered as an example to explain the process of drug recommendation. Because diabetes is one of the leading causes of death, semantic knowledge of this disease is expanded, and it is difficult to efficiently interact with and share that knowledge. In order to provide such a drug and food recommendation service, intelligent semantic knowledge and medical terminologies are needed. Using OWL, a drug ontology is developed that expresses well-known medical terminology in order to assign drugs automatically, according to the patient test results. Besides medical terminology, components and annotations (explanations) are expressed in the ontology in order to make it easily understandable for new doctors and nurses. Common names are used in the ontology for identification, and an example for gliclazide is shown in Fig. 9. Diabetes drugs are divided into two categories: insulin and oral medications. This system only considers oral medications, because the drugs are assigned to the smart medicine box, since some patients fear injections. In addition, the diabetes drugs class is divided into three subclasses: components, Low-Drugs, Medium-Drugs and High-Drugs. The Low-Drugs class contains drugs that decrease the amount of blood sugar produced by the liver, such as metformin (a biguanide) and thiazolidinedione. The Medium-Drugs class stores medications that prevent the breakdown of food into sugar, such as alpha-glucosidase inhibitors. The High-Drugs class contains medications that increase insulin production in the body, such as dipeptidyl peptidase 4 (DPP-4) inhibitors (saxagliptin, sitagliptin), meglitinides (repaglinide, nateglinide) and sulfonylureas (glipizide, glimepiride, and glyburide). In addition, there are three main classes in the drugs ontology: the smart medicine box, the home drug repository, and hospital drugs. The smart medicine box contains daily drugs. A small sensor is fixed inside the smart medicine box to routinely check the drug types and quantities. The system assigns a drug to the smart medicine box from the home or hospital drug repository, according to the patient's condition. The home drug repository has different types of drug classes, such as Very-Low, low, medium, High and Very-High for each disease. The hospital drug class stores emergency medicine and medical equipment. There are so many health problems for diabetes patients; some are easily curable, and some are not curable from the home drug repository. Therefore, the hospital drug class provides emergency medicine and emergency healthcare services. Every medicine and healthcare service is analyzed. The doctor makes a plan for treatment, and here, the doctor expresses what medicines and healthcare services are to be given to the patient. Emergency healthcare services include not only those provided in-hospital but also those provided outside the hospital, such as drug and equipment supplies. Physicians can access the patient data and drug history from the patient and sensor ontology for emergency services. However, physicians also need equipment data to know its busy/free status and its location. Currently, IoT technology is widely used in emergency healthcare services [18,19]. For example, a bar code is used to label the medicine so the correct medicine is delivered to the patient. The equipment is connected using a global positioning system (GPS) and radio frequency identification (RFID) to find it quickly. In order to support this heterogeneous data sharing, flexible semantic knowledge is needed to assist physicians during emergency healthcare. This semantic knowledge is provided by the proposed ontology. The drug ontology represents the relationships of the patient and the anti-diabetes drug classes. This ontology needs information and important medical instructions; therefore, the SWRL rules plugin is used to edit these instructions. These instructions or rules use easy syntax that can be understood by both the system and humans. The drug recommendations also depend on various factors about the diabetes patient, such as sex. For example, in pregnancy, the diabetes patient cannot take diabetes pills because oral medications can cross the placenta. Therefore, these kinds of instructions are also encoded in the rules. The above rules are prescribed only for patient condition value computation, whereas the following rules are made for drug recommendations.

Rule 1: Patient(?X), isPatientOf(?X, BloodSugar), isnotPatientOf(?X, Pregnancy), HasAge(?X, Mild), HasAge(?X, Old), HasAge(?X, VeryOld), HasBloodSugarSensorTestResult(?X, BSVHigh),

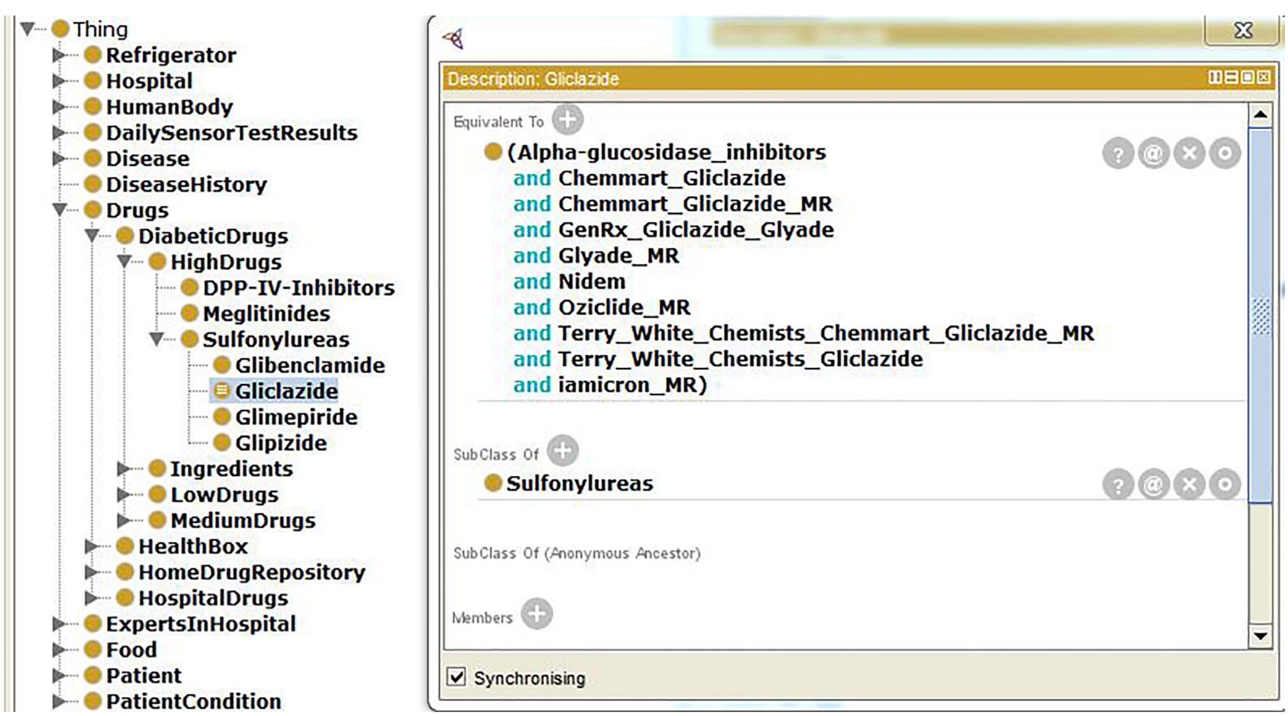


**Fig. 9.** Components of diabetes drugs.

HasLiverTest(?X, Positive), greaterThan(?BSVHigh, 200), equal (?Positive, 1) -> DrugTake(?X, Metformin)
Rule 2: Patient(?X), isPatientOf(?X, BloodSugar), isnotPatientOf(?X, Pregnancy), HasAge(?X, Mild), HasAge(?X, Old), HasAge(?X, VeryOld), HasBloodSugarSensorTestResult(?X, BSHigh), HasL iverTest(?X, Positive), greaterThan(?BSHigh, 140), lessThan (?BSHigh, 200), equal(?positive, 1) -> DrugTake(?X, Thaizolidinediones)
Rule 3: Patient(?X), isPatientOf(?X, BloodSugar), isnotPatientOf(?X, Pregnancy), HasAge(?X, Mild), HasAge(?X, Old), HasBloodSugarSensorTestResult(?X, BSMedium), HasLiverTest(?X, Positive), greaterThan(?BSMedium, 75), lessThan(?BSMedium, 160), equal(?positive, 1) -> DrugTake(?X, alpha-glucosidase-inhibitors)
Rule 4: Patient(?X), isPatientOf(?X, BloodSugar), isnotPatientOf(?X, Pregnancy), HasAge(?X, Mild), HasAge(?X, Old), HasBloodSugarSensorTestResult(?X, BSLow), HasLiverTest(?X, Positive), greaterThan(?BSLow, 30), lessThan(?BSLow, 90), equal (?positive, 1) -> DrugTake(?X, DPP-IV-Inhibitors) -> DrugTake(?X, Sufonylureas)
Rule 5: Patient(?X), isPatientOf(?X, BloodSugar), isnotPatientOf(?X, Pregnancy), HasAge(?X, Mild), HasAge(?X, Old), HasBloodSugarSensorTestResult(?X, BSVLow), HasLiverTest(?X, Positive), greaterThan(?BSVLow, 0), lessThan(?BSVLow, 45), equal (?positive, 1) -> DrugTake (?X, Meglitinide)

The Protégé 4.3 package reasoners, such as Pellet, Fact++++, and Hermit, are used to find ambiguities in the recommendation ontology. The classic ontology is unable to express vagueness data; therefore, the recommendation ontology is converted to a fuzzy recommendation ontology. Matlab was used to implement the mathematical requirements for computation of the patient health condition value. In Section 5.2, the input variables, along with a range, are defined for patient monitoring. Some restrictions are encoded before the execution of diabetes drug recommendation rules. First, the patient blood sugar test result should be in the range of Very-Low (0 ~ 45), Low (30 ~ 90), High (140 ~ 200), and Very-High (180 ~ 300). Second, the liver test result should be positive (abnormal). Third, the patient should not be pregnant. If the patient is pregnant, the recommendation system will not run. The patient kidney test result should be abnormal (amounts of protein from blood in the urine should be abnormal). After the extraction of these parameters, the system can recommend diabetes drugs to the patient.

The recommendation of healthy food is a very important factor for controlling diabetes. It could only be possible if the nutrition expert prepares foods for each diabetes patient. However, nutrition experts are unable to prepare food for all diabetes patients. In a smart world, semantic knowledge is needed to define the combinations of foods for diabetes patients, and to assign foods automatically according to the patient's health condition. Some research work has been done, which recommends foods for diabetes patients using an ontology. However, using only a classic ontology and diabetes food is not enough, because efficient classifications of these foods are needed. In addition, the functionality of other body parts should also be measured. This food recommendation system contains a food ontology and a smart refrigerator. The food ontology is knowledge of foods, which can provide a list of food for diabetes patients, as shown in Fig. 10.

The Calories class in the food ontology has three instances (High-Calories, Medium-Calories, and Low-Calories) which are used during food recommendation. The food ontology retrieves the patient's personal data (age, height, and weight) from the patient ontology and the movement speed of the body from the sensor ontology. These data are used to determine the basal metabolic rate (BMR) and daily calorie needs for blood sugar in the patient. Eqs. (13) and (14) (Harris–Benedict) are used to calculate the BMR for males and females, respectively [63].

$$BMR = 10*weight\,(kg) + 6.25*height\,(cm) - 5*age\,(y) + 5 \tag{13}$$

$$BMR = 10*weight\,(kg) + 6.25*height\,(cm) - 5*age\,(y) + 161 \tag{14}$$

The BMR calculates the daily calorie needs. The activities of the diabetes patient provide a supporting factor in determining the daily calorie needs [64]. In this ontology, five instances are described to express diabetes patient activities. These instances, along with numerical values, are sedentary lifestyle = 0.2, slightly active = 1.37, moderately active = 1.55, active life style = 1.725, and very active life style = 1.9. Multiplication of the numerical value and the BMR gives the total number of calories needed to maintain the current condition of the diabetes patient. For example, if the diabetes patient has a sedentary lifestyle, then the total daily calories are BMR x 1.2. Once the number of calories to maintain the weight of the diabetes patient is calculated, the system can easily recommend healthy foods. The smart refrigerator is divided into three parts that contain different types of foods, such as low-calorie foods, medium-calorie foods, and high-calorie foods. Small sensors are fixed on top of each part, which provide a green signal to help the diabetes patient during healthy food selection. These foods are assigned to each part based on semantic knowledge of the food ontology. This system uses various rules to recommend healthy foods. Some of the rules are as follows.

Rule 1: Name (?X), isPatientOf(?X, BloodSugar), HasCalories(?X, Maintain) -> FoodTake(?X, Medium-Calories)
Rule 2: Name (?X), isPatientOf(?X, BloodSugar), HasCalories(?X, Lose) -> FoodTake(?X, low-Calories)
Rule 3: Name (?X), isPatientOf(?X, BloodSugar), HasCalories(?X, High) -> FoodTake(?X, high-Calories)
Rules 1, 2, and 3, respectively, are utilized as follows: 1) if blood sugar calories should be maintained, then the medium-calorie food should be selected; 2) if calories should be decreased, then the low-calorie food should be selected; and 3) if calories should be increased, then high-calorie food should be selected.

## 6. Experiment and results

To evaluate the performance of the proposed system, T2FSs were implemented in Matlab, which can get input from wearable sensors to find the risk value for a diabetes patient. Protégé OWL was used to develop semantic knowledge for decision-making. Our experimental environment used an Intel Core i7-2600 CPU with 8 GB RAM and the Windows 7 operating system. The evaluation process was divided into three phases: ontology evaluation, a comparison between our proposed system and other systems, and measurement of the overall system efficiency.

### 6.1. Ontology evaluation and system accuracy computation

The performance of the proposed ontology was evaluated after the development of each phase to measure the improvement level. Evaluation of an ontology is essential, because the ontology information automatically declares the instances that might be duplicated or might not be identical. A well-known method is used to evaluate an ontology in the form of questions and answers, such as the DL query and SPARQL query [65]. A DL query of Protégé is a dynamic and user-friendly plugin to construct valid instances or individuals in the required time for the input query. A SPARQL query combines the variables and properties to extract the needed instances or individuals. The DL and SPARQL queries are defined in the OWL syntax. Reasoners such as Pellet, Fact++++, Hermit, and RacePro must be run before any query execution. The Pellet reasoner was executed to evaluate this ontology. It is based on the Apache Jena application programming interface and allows users to write rules that are more complex. The proposed ontology has a lot of vagueness, because diabetes patient health information is always

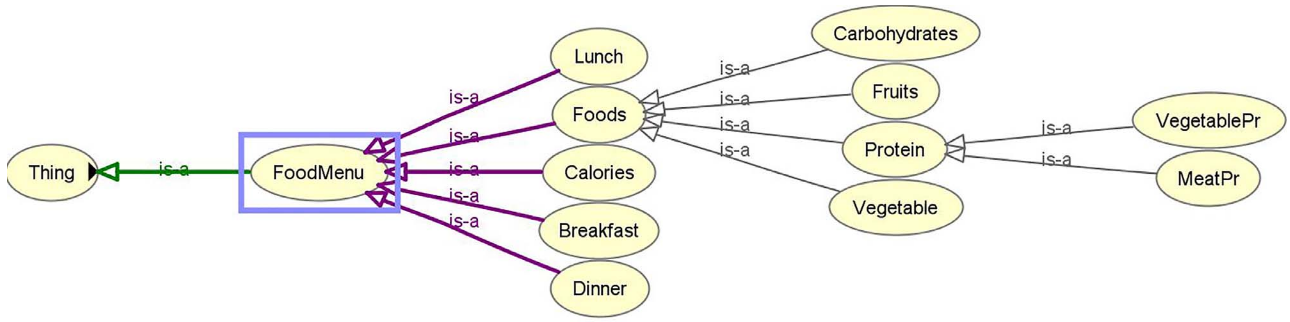


**Fig. 10.** Food ontology concept.

uncertain. Therefore, the Pellet reasoner converted the fuzzy ontology into a classic ontology and analyzed the performance of the proposed ontology. Various queries were designed to evaluate the overall efficiency of the system and to retrieve the instances. These queries are as follows.

DL query 1:

Syntax: *If only (HasBloodPressureSensorTestResult value BPVHigh and HasBloodSugarSensorTestResult value BSVHigh and HasCholesterol SensorTestResult value CHVHigh and HasECGSensorTestResult value ECGRateVHigh)*

Explanation: In the above query, the ontology analyst wants to find the patient name along with the disease name, where sensor test results are very high. The ontology extracts the needed information according to the input query. The output of this query is dependent on both the input query and wearable sensors of the patient. The output of this query in Fig. 11 and Table 2 shows that ‘Goro’ is a patient with a high-level rate for diabetes and heart.

DL query 2:

Syntax: *HasBloodSugarSensorTestResult value BSVHigh and HasLiverTest value Positive and Drugs*

Explanation: In the above query, the system attempts to extract the drugs for a diabetes patient whose blood sugar is very high and whose liver test is positive. *BSVHigh* and *Positive* are the linguistic terms of the fuzzy variable *Blood Sugar* and *Liver Test*, while *Drugs* is a class name that contains drug information. The output of this query in Fig. 12 and Table 2 shows that *Metformin* is a drug for patients whose blood sugar is very high and whose liver test is positive.

SPARQL query 3:

Syntax:

**Table 2**
The output of evaluation queries 1–3.

| The output of evaluation query 1 and 2 | | | The output of evaluation query 3 | | |
|---|---|---|---|---|---|
| | Instances | Direct super classes | Name | Drugs | Patient health condition |
| DL query 1 | Goro | Diabetes<br>Heart | Goro<br>Diahann Chan | Metformin<br>Thiazolidinedione | Serious<br>Serious |
| DL query 2 | Metformin | Diabetes<br>Drugs | Robin<br>Romain | Metformin<br>Metformin | Serious<br>Serious |

*SELECT ?Name?Drugs?PatientCondition*
*WHERE{?Name rdfs:subClassOf ?NamePatient.*
*?Name Result:IsPatientOf ?Diabetics.*
*?BloodSugar rdf:type ?HasBloodSugarSensorTestResult.*
*?BloodSugar Result:BSVHigh ? Diabetics.*
*?Drugs rdfs: subClassOf ?DiabeticDrugs.*
*?Drugs Result:DrugTake ?NamPatient.*
*?PatientCondition rdfs:subClassOf ?DiabetesPatient.*
*?PatientCondition Result:HasBloodSugarSensorTest ?DailySensor TestResult.}*

Explanation: This query shows the patient name, drugs recommended, and the patient health condition level according to the blood sugar sensor test results. The results of this SPARQL query for the ontology analyst input query (“show the name of those patients who take the high-level diabetes drugs”) are shown in Table 2.


**Fig. 11.** The output of DL query 1.

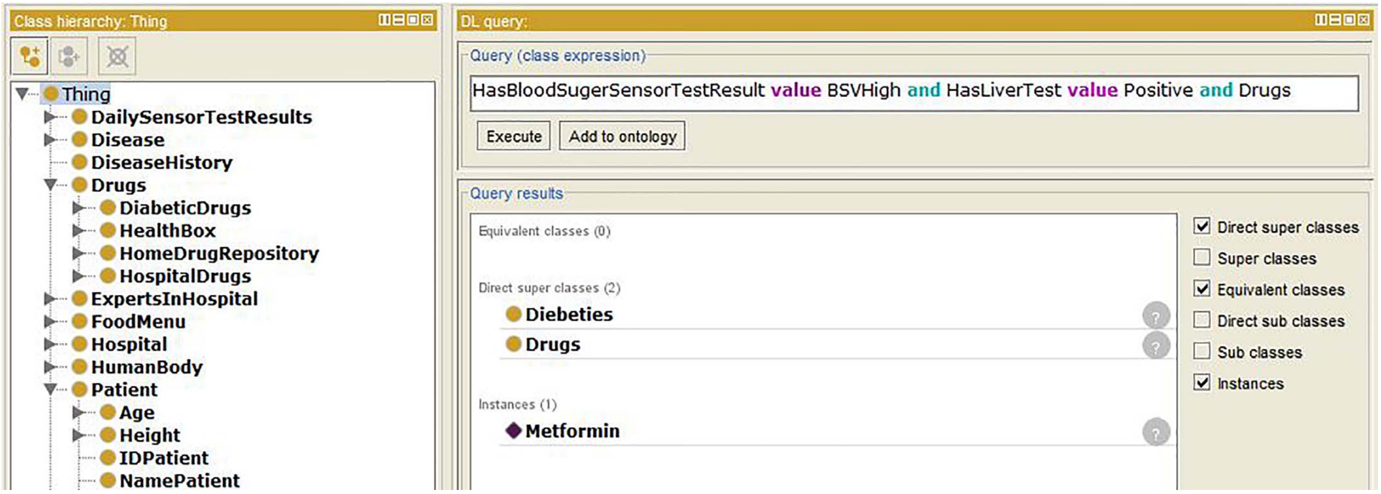


**Fig. 12.** The output of DL query 2.

### 6.2. A T1FL and T2FL-based systems evaluation

Most of the existing diabetes patient health monitoring and recommendation systems are based on a classic ontology and type-1 fuzzy logic. The existing T1FL-based systems have various inputs and one output to diagnose heart disease [14,24,47]. However, these existing systems are unable to extract the correct membership value from each input, and therefore, that affects the overall results. A classic ontology with a rules-based system is presented for diabetes management to enhance accuracy [47]. However, these systems are insufficient at defining fuzzy terms of patient factors (e.g., blood sugar {high, medium, low}). It is notable that these systems can determine the patient health value to some extent. However, they cannot perfectly monitor patients when there is intensive uncertainty in patient risk factors. They do not provide sufficient information to physicians and patients. In addition, there is a need for decision-making knowledge for IoT-based healthcare to automate the monitoring and recommendation process. A T2FS and fuzzy ontology have not been used before to compute the health condition value of a diabetes patient and to recommend foods and drugs. However, they have been used to develop other healthcare systems for diabetes patients.

In our experiment, T1FL and T2FL are used to compute 44 diabetes patient health values with varying conditions for blood sugar (BS), blood pressure (BP), cholesterol (CH), heart rate (HR), body movement (BM), age, and weight. Both the systems performed well for most types of patient health conditions, e.g. Healthy (0.0 ~ 5.0), Moderate (2.5 ~ 7.5) and Serious (5.0 ~ 10). The computed health values using T1FL and T2FL were compared with expert decisions to determine which results mostly matched the experts. Agree and disagree counts in the data between the proposed system and the experts are shown in Table 3, and the T1FL-based system versus expert counts are shown in Table 4. Agreement between the systems and the experts was measured by Cohen's Kappa coefficient equation, as follows [13]:

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)} \tag{15}$$

**Table 3**
Estimations by the proposed system and by experts.

| The proposed T2FL-based system | Experts | |
|---|---|---|
| | Agree | Disagree |
| Agree | 10 | 0 |
| Disagree | 1 | 33 |

**Table 4**
Estimations by a T1FL-based system and by experts.

| T1FL-based system | Experts | |
|---|---|---|
| | Agree | Disagree |
| Agree | 9 | 3 |
| Disagree | 2 | 30 |

where Pr (a) denotes the actual observed agreement, and Pr (e) denotes chance agreement. If both completely agree, then K = 1, and if there is no agreement, then K = 0. After using T2FL, the relative observed agreement is $\Pr(a) = \frac{10+33}{44} = 0.977$, and the hypothetical probability of chance agreement $\Pr(e) = 0.64$. Thus, the overall probability of agreement between the proposed system and the experts is as follows.

$$K = \frac{0.977 - 0.64}{1 - 0.64} = \frac{0.337}{0.36} = 0.936 = 93.6\%$$

In addition, the precision of the recommendation system was computed with Eq. (16), where TP (True Positive) represents the expert is in agreement, and FP (False Positive) signifies the expert disagrees on the recommended items. The agreement calculation results for the proposed system and the experts is 93.6%, while the result for the T1FL-based system and the experts is 75.2%. These results show that our system has better performance than a T1FL-based system. Table 5 results assert that the accuracy of our proposed system's prediction is good, and the precision rate of our recommendation system is 100%. It can be used for IoT-based healthcare, because it meets doctor and patient requirements.

### 6.3. The overall system performance measurement

In this experiment, diabetes patients with varying conditions used wearable sensors to make inquiries of the proposed system. In addition, different types of queries were designed for each patient in order to extract the needed information from semantic knowledge. The system writes the patients' records for performance metrics as *precision, recall, accuracy,* and *function measure*. These metrics are used to evaluate the performance of prediction methods used in the experiments [66]. *Precision* measures the degree of closeness of two or more decisions each other, while *accuracy* describes the degree of closeness of a measured value to a targeted value or known value. At first, a classic ontology is used during the process of patient health-level prediction and recommendation, and the *precision, recall, accuracy,* and *function measure* are recorded. Later, T1FL with a classic ontology, and T2FL with a fuzzy

**Table 5**
System performance evaluation based on T2FL.

| No | Blood sugar (BS) | Blood pressure (BP) | Cholesterol (CH) | Heart rate (HR) | Body movement (BM) | Age | Weight | The proposed system-based health value | Patient health condition | Food and drug recommendation ontology precision |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 190 | 130 | 210 | 88 | 33 | 54 | 94 | 8.79 | Serious | 100% |
| 2 | 140 | 130 | 225 | 85 | 29 | 27 | 80 | 4.86 | Moderate | 100% |
| 3 | 130 | 120 | 200 | 70 | 20 | 51 | 76 | 3.95 | Healthy | 100% |
| 4 | 150 | 110 | 240 | 90 | 43 | 56 | 61 | 5.98 | Moderate | 100% |
| 5 | 160 | 120 | 250 | 95 | 50 | 52 | 69 | 6.25 | Moderate | 100% |
| 6 | 170 | 130 | 260 | 65 | 25 | 54 | 79 | 7.33 | Serious | 100% |
| 7 | 180 | 140 | 250 | 80 | 19 | 72 | 58 | 6.51 | Serious | 100% |
| 8 | 210 | 160 | 210 | 75 | 34 | 61 | 82 | 7.81 | Serious | 100% |
| 9 | 160 | 180 | 250 | 77 | 19 | 66 | 53 | 8.35 | Serious | 100% |
| 10 | 145 | 150 | 160 | 67 | 25 | 53 | 56 | 2.59 | Healthy | 100% |

ontology are used to compute the results. In each case, the health condition values and query results for each patient are compared with information provided by the experts. Eqs. (16)–(19) were used to calculate the metrics.

$$Precision\,(Pre) = \frac{TP}{TP + FP} \tag{16}$$

$$Recall\,(Re) = \frac{TP}{TP + FN} \tag{17}$$

$$Accuracy\,(Acc) = \frac{TP + TN}{TP + TN + FP + FN} \tag{18}$$

$$Function\ measure\,(FM) = \frac{2{*}precision{*}recall}{precision + recall} \tag{19}$$

Here, TP, FP, TN, and FN, respectively, indicate the number of true positives (correctly predicted diabetic patient level and extracted true recommended items among the referred items), the number of false positives (incorrectly predicted diabetic patient level and extracted false recommended items among the referred items), the number of true negatives (correctly predicted non-diabetic and pre-diabetic patient levels and extracted true recommended items among the referred items), and the number of false negatives (diabetic patient level incorrectly predicted as a non-diabetic or pre-diabetic patient level and extracted false recommended items among the referred items). FM is a composite measure, which is mostly used to evaluate prediction accuracy, counting both precision and recall. Table 6 shows the precision, recall, accuracy, and function measure results pertaining to various diabetes patient recommendation items for a classic ontology, T1FL with a classic ontology, and T2FL with a classic ontology. The results of the classic ontology were compared with the proposed system results. It is seen that the precision, accuracy, and function measure rates increased from 54% to 97%, from 61% to 83%, and from 59% to 89%, respectively. Moreover, the recall rate is higher than the precision rate with the classic ontology. The recall rate largely decreased, compared to precision with the proposed system. The results of our proposed system proved that the diabetes patient information can be achieved more precisely, and the system can recommend foods and drugs efficiently using T2FL with a fuzzy ontology. Fig. 13 clearly describes the performance analysis between the classic ontology, T1FL with the classic ontology, and T2FL with the fuzzy ontology. It illustrates that the average precision, accuracy, and function measure rates significantly increased during the diabetes patient monitoring and recommendation processes with T2FL and the fuzzy ontology.

## 7. Conclusion

This paper presents type-2 fuzzy logic and fuzzy ontology–based semantic knowledge to automate the detection of physiological risk factors about a patient's body and the required diabetes prescriptions. A number of realistic issues are efficiently considered; for example, extraction of a patient's personal data and disease history, detection of risk factors using wearable sensors, prediction of a patient's health condition by employing T2FL, declaration of semantic knowledge by utilizing a fuzzy ontology, and the recommendation of food and drugs using a smart refrigerator and a smart medicine box. The proposed system increases the performance of a chronic patient healthcare system. This system can effectively overcome the load of chronic patients on hospitals, help physicians to automatically retrieve patient physiological information for diagnoses, and can assist old patients with chronic diseases for long-term care without continuous visits to physicians. This system can be applied to the existing IoT-based healthcare monitoring architecture, because it has the ability to control dietary and diabetes drug recommendations. In future work, the detection procedure for health conditions will be further enhanced in the field of

**Table 6**
The proposed system results in cases of classic ontology, T1FL with classic ontology and T2FL with fuzzy ontology.

| Diabetes patients | Total extracted recommended items (foods and drugs) | Classic ontology-based system [1,15] | | | | T1FL with classic ontology-based system [8,22,24] | | | | The proposed system based on T2FL and fuzzy ontology | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Pre (%) | Re (%) | Acc (%) | FM (%) | Pre (%) | Re (%) | Acc (%) | FM (%) | Pre (%) | Re (%) | Acc (%) | FM (%) |
| 1 | 234 | 47 | 53 | 56 | 50 | 83 | 77 | 78 | 80 | 99 | 77 | 77 | 87 |
| 2 | 331 | 42 | 69 | 60 | 52 | 89 | 82 | 80 | 85 | 99 | 82 | 83 | 90 |
| 3 | 355 | 47 | 66 | 57 | 55 | 80 | 64 | 63 | 71 | 100 | 83 | 84 | 91 |
| 4 | 312 | 55 | 69 | 62 | 61 | 82 | 67 | 67 | 74 | 97 | 75 | 77 | 84 |
| 5 | 290 | 63 | 66 | 62 | 65 | 84 | 63 | 61 | 72 | 97 | 82 | 84 | 89 |
| 6 | 282 | 66 | 70 | 67 | 68 | 88 | 63 | 65 | 73 | 99 | 82 | 83 | 89 |
| 7 | 300 | 58 | 64 | 58 | 61 | 88 | 61 | 61 | 72 | 99 | 84 | 86 | 91 |
| 8 | 261 | 49 | 76 | 63 | 59 | 82 | 62 | 63 | 70 | 96 | 85 | 85 | 90 |
| 9 | 251 | 56 | 73 | 63 | 64 | 86 | 71 | 73 | 78 | 95 | 86 | 87 | 90 |
| 10 | 378 | 54 | 69 | 64 | 60 | 81 | 63 | 63 | 71 | 98 | 77 | 80 | 86 |
| Average | | 54 | 67 | 61 | 59 | 84 | 67 | 68 | 75 | 97 | 81 | 83 | 89 |

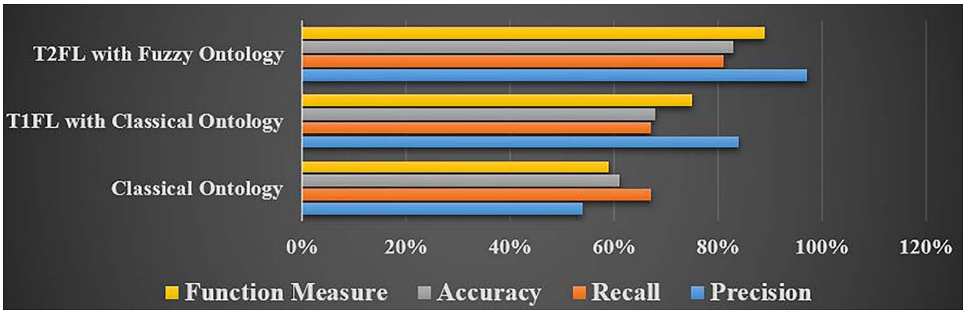


**Fig. 13.** Graphical comparison between classic ontology–based systems, T1FL with classic ontology--based systems, and the proposed system.

healthcare monitoring and diabetes prescriptions.

Our future work will also focus on using a type-2 fuzzy neural network and ontology-based sentiment analysis for a treatment recommendation system. Indeed, such a system is needed that can efficiently find the polarity of medicine-related tweets to recommend specific drugs in a limited time. In this system, a neural network with type-2 fuzzy ontology-based semantic knowledge can be considered to facilitate the information retrieval from social network and to identify the diseases. For information extraction and retrieval in sentiment analysis, we may propose to use the support vector machine that is more effective to filter out irrelevant data.

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