A Fuzzy Expert System for Diabetes Decision Support Application

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***Abstract*—An increasing number of decision support systems based on domain knowledge are adopted to diagnose medical conditions such as diabetes and heart disease. It is widely pointed that the classical ontologies cannot sufficiently handle imprecise and vague knowledge for some real world applications, but fuzzy ontology can effectively resolve data and knowledge problems with uncertainty. This paper presents a novel fuzzy expert system for diabetes decision support application. A five-layer fuzzy ontology, including a fuzzy knowledge layer, fuzzy group relation layer, fuzzy group domain layer, fuzzy personal relation layer, and fuzzy personal domain layer, is developed in the fuzzy expert system to describe knowledge with uncertainty. By applying the novel fuzzy ontology to the diabetes domain, the structure of the fuzzy diabetes ontology (FDO) is defined to model the diabetes knowledge. Additionally, a semantic decision support agent (SDSA), including a knowledge construction mechanism, fuzzy ontology generating mechanism, and semantic fuzzy decision making mechanism, is also developed. The knowledge construction mechanism constructs the fuzzy concepts and relations based on the structure of the FDO. The instances of the FDO are generated by the fuzzy ontology generating mechanism. Finally, based on the FDO and the fuzzy ontology, the semantic fuzzy decision making mechanism simulates the semantic description of medical staff for diabetes-related application. Importantly, the proposed fuzzy expert system can work effectively for diabetes decision support application.**

***Index Terms*—Decision support agent, diabetes application, fuzzy expert system, fuzzy ontology, semantic web.**

I. Introduction

DIABETES, a chronic illness, requires continuous medical care and patient self-management education to prevent acute complications and to decrease the risk of long-term complications. Diabetes treatment focuses on controlling blood sugar levels to prevent various symptoms and complications through medicine, diet, and exercise. The American Diabetes Association [1] categorizes diabetes into type-1 diabetes, which is normally diagnosed in children and young adults, and type-2 diabetes, i.e., the most common form of diabetes that originates from a progressive insulin secretory defect so that the body does not produce adequate insulin or the insulin does not affect the cells. Either the fasting plasma glucose (FPG) or the 75-g oral glucose tolerance test (OGTT) is generally appropriate to screen diabetes or pre-diabetes. Additionally, the cause of diabetes has not been identified, and it is also affected by an uncertain environment. Therefore, both genetics and environmental factors, e.g., obesity, race, gender, age, and lack of exercise, apparently play important roles in the diagnosis of diabetes. The increasing number of diabetics worldwide has drawn the attention of a diverse array of fields, including artificial intelligence and biomedical engineering, explaining why related technologies such as fuzzy inference mechanisms and fuzzy expert systems have been adopted for diabetes research. For instance, Campos-Delgado *et al.* [2] developed a fuzzy-based controller that incorporates expert knowledge to regulate the blood glucose level. Magni and Bellazzi [3] devised a stochastic model to extract variability from a self-monitoring blood sugar level time series. Polat and Gunes [4] designed an expert system to diagnose the diabetes disease based on principal component analysis. Polat *et al.* [5] also developed a cascade learning system to diagnose the diabetes. Chang and Lilly [6] developed an evolutionary approach to derive a compact fuzzy classification system. Goncalves *et al.* [7] introduced an inverted hierarchical neuro-fuzzy BSP system for pattern classification and rule extraction in databases. Kahramanli and Allahverdi [8] designed a hybrid neural network system for classification of the diabetes database.

Capable of modeling the concepts in a domain and describing the relationships among concepts, ontology has been extensively studied in many research fields, including multi-agent systems, natural language processing, medicine, and e-commerce platforms. For instance, Cranfield and Pan [9] described relations between model-driven architecture and ontology engineering. By using ontology, Weng and Chang [10] constructed user profiles in research and then made a research document recommendation. Lee *et al.* [11], [12] proposed an ontology-based intelligent decision support agent for capability maturity model integration (CMMI) applications and an automated ontology construction for unstructured text documents. Yager and Petry [13], [14] developed a multicriteria approach to data summarization using concept ontologies and a framework for the resolution of apparently contradictory evidence for decision making. Buche *et al.* [15] designed a fuzzy querying scheme for incomplete, imprecise, and heterogeneously structured data in the relational model using ontologies and rules. Bechhofer *et al.* [16] used ontologies and vocabularies for dynamically linking to solve some problems with static, restricted, and inflexible traditional web. Moreover, as a physical or virtual entity, an agent can act in an environment and communicate directly with other agents. Recent advances in semantic web and Internet-based technologies have accelerated the burgeoning growth of research on intelligent agents. For instance, Pedrycz and Rai [17] presented collaborative intelligent agents for data analysis. Corchado *et al.* [18] developed

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an ambient intelligence scheme to dynamically schedule nursing tasks, report on their activities, and monitor patient care. Grelle *et al.* [19] proposed an architecture using the agent paradigm as a simple and powerful bridge to design a complex hybrid control environment. Lee and Wang [20] designed an ontology-based intelligent healthcare agent for respiratory waveform recognition. Lee *et al.* [21] also developed a genetic fuzzy agent for meeting scheduling system.

However, as is well known, classical ontology cannot adequately represent imprecise and vague knowledge, leading to the evolution of fuzzy ontology to handle this knowledge in several real world applications. For instance, Calegari and Farina [22] developed fuzzy ontologies and scale-free networks analysis. Lee *et al.* [23] designed a fuzzy ontology and then applied it to news summarization. Quan *et al.* [24] proposed an automatic fuzzy ontology generation for semantic help desk support. Knappe *et al.* [25] designed an ontology-based query enrichment approach. Hudelot *et al.* [26] proposed a fuzzy spatial relation ontology for interpreting images. Quan *et al.* [27] developed an automatic fuzzy ontology generation approach for semantic web. This paper presents a novel five-layer fuzzy ontology and then extends the fuzzy ontology model to construct the fuzzy diabetes ontology (FDO) with diabetes domain. A novel FDO-based fuzzy expert system for making diabetes-related decisions is composed of a novel five-layer fuzzy ontology, FDO, and a semantic decision support agent (SDSA). Additionally, the SDSA consists of a knowledge construction mechanism, fuzzy ontology generating mechanism, and semantic fuzzy decision making mechanism. The proposed fuzzy expert system can give a semantic description for diabetes and support for the justification of the medical staff. Experimental results indicate that the proposed fuzzy expert system can work more effectively than other methods can [4], [5], [8].

The remainder of this paper is organized as follows. Section II introduces the five-layer fuzzy ontology and FDO. Section III then describes the architecture of the FDO-based expert system for diabetes application and the knowledge construction mechanism. Next, Section IV introduces the fuzzy ontology generating mechanism and the semantic fuzzy decision making mechanism for diabetes application. Section V summarizes the experimental results. Conclusions are finally drawn in Section VI, along with discussions over future works.

II. Definition of Fuzzy Ontology

This paper presents a novel fuzzy expert system, including a novel five-layer fuzzy ontology based on fuzzy numbers, to describe the fuzzy concepts and fuzzy relations for diabetes-related applications. The proposed five-layer fuzzy ontology is an extended version from the domain ontology in [12] and the fuzzy ontology in [23] and [31]. This section first describes the definitions and structure of the novel fuzzy ontology. The proposed fuzzy ontology model is then extended to describe diabetes domain knowledge based on the Pima Indians Diabetes Database (PIDD) [28]. Finally, the definition and structure of the FDO are presented.

A. Five-Layer Fuzzy Ontology

Definition 1—Fuzzy Ontology Ω_F: A fuzzy ontology Ω_F describes the domain knowledge with uncertainty. This model is an extension of the domain ontology [12] and contains five layers, i.e., a fuzzy knowledge layer, fuzzy group relation layer, fuzzy group domain layer, fuzzy personal relation layer, and fuzzy personal domain layer. The concepts and relations of the fuzzy ontology are constructed by fuzzy variables and fuzzy numbers, respectively. That is, a fuzzy variable, including some fuzzy numbers, is used to represent a fuzzy concept. Additionally, the relations in the fuzzy group relation layer and the fuzzy personal relation layer are constructed by the fuzzy numbers. ■

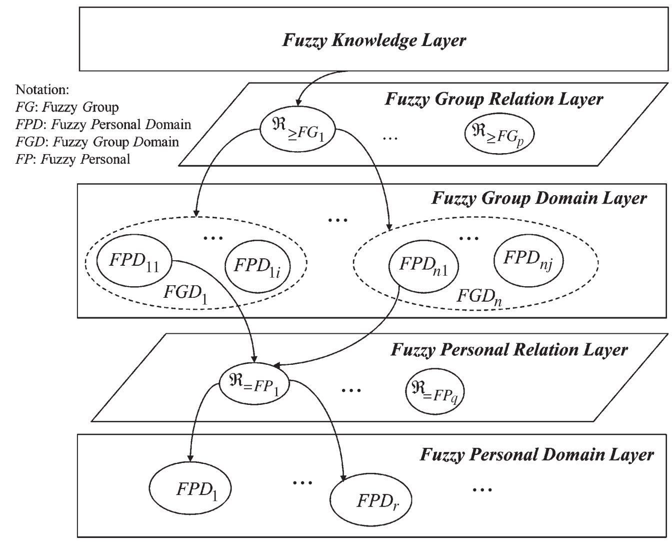

Fig. 1. Structure of the novel five-layer fuzzy ontology.

Fig. 1 shows the structure of the proposed novel five-layer fuzzy ontology. The fuzzy group relation layer contains p fuzzy group relations, such as $\Re_{\geq FG_1}, \ldots$ and $\Re_{\geq FG_p}$. The fuzzy group domain layer has n fuzzy group domains (FGDs), including $FGD_1, \ldots$ and FGD_n. Each FGD consists of various fuzzy personal domains (FPDs). For instance, if FGD_1 comprises i PFDs, then we denote them as $FPD_{11}, \ldots$ and FPD_{1i}, respectively. The fuzzy personal relation layer has q relations, like $\Re_{=FP_1}, \ldots$ and $\Re_{=FP_q}$. The final layer, fuzzy personal domain layer, has r FPDs, for example, $FPD_1, \ldots$ and FPD_r. The following definitions introduce in detail the proposed fuzzy ontology.

Definition 2—Fuzzy Knowledge Layer: A fuzzy knowledge layer contains a fuzzy knowledge domain name, various categories of the fuzzy domain, and fuzzy concept sets. The concept sets contain some fuzzy variables. Each fuzzy variable in the concept sets has some fuzzy numbers to describe the characteristics of the fuzzy variable. ■

Definition 3—Fuzzy Group Relation $\Re_{\geq FG}$: A fuzzy group relation, denoted by $\Re_{\geq FG}$, extends the instance-of relation that describes the "greater than" relationship between the fuzzy concept in the fuzzy knowledge layer and its specific instance in the fuzzy group domain layer using a fuzzy number. For a fuzzy concept set K_C of the fuzzy knowledge layer and an instance set I_G of the fuzzy group domain layer, any subset of $K_C \times I_G$ is called an $\Re_{\geq FG}$ from K_C to I_G. ■

Definition 4—Fuzzy Group Domain Layer: A fuzzy group domain layer is a specific fuzzy knowledge layer that includes the concepts of the instances with specific properties and a similar relation defined in the fuzzy ontology. ■

TABLE I
ATTTRIBUTES OF PIDD

Abbreviation	Full Name	Unit
Pregnant	Number of times pregnant	-
Glucose	Plasma glucose concentration in a 2-hour OGTT	mg/dl
DBP	Diastolic blood pressure	mmHg
TSFT	Triceps skin fold thickness	mm
INS	2-hour serum insulin	mu U/ml
BMI	Body mass index	kg/m^2
DPF	Diabetes pedigree function	-
Age	Age	-
DM	Diabetes Mellitus, where "1" is interpreted as "tested positive for diabetes."	-

Definition 5—Fuzzy Personal Relation $\Re_{=FP}$: A fuzzy personal relation, denoted by $\Re_{=FP}$, extends the instance-of relation that describes the relationship between the fuzzy concept in the fuzzy group domain layer and its specific instance in the fuzzy personal domain layer by using a fuzzy number. For a fuzzy concept set I_G of the fuzzy group domain and an instance set I_P of the fuzzy personal domain layer, any subset of $I_G \times I_P$ is called an $\Re_{=FP}$ from I_G to I_P. ■

Definition 6—Fuzzy Personal Domain Layer: A fuzzy personal domain layer is a specific fuzzy knowledge layer that includes the concepts of the instances with the same fuzzy number properties defined in the fuzzy ontology. ■

B. Pima Indians Diabetes Database

The National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) [28] has examined the Pima Indians for the past three decades. This group has one of the highest known rates of diabetes worldwide. While studying Pima Indian volunteers, a related study found that an unhealthy weight is a strong predictor of diabetes. According to NIDDK's experimental results, a high level of insulin in the blood is another strong risk factor to develop diabetes and NIDDK even found that diabetes is hereditary. The experimental PIDD is retrieved from the Internet (http://archive.ics.uci.edu/ml/) and it contains the collected personal data of the Pima Indian population. Table I lists the attributes of PIDD.

C. Structure of Fuzzy Diabetes Ontology

Based on the attributes of the PIDD listed in Table I and the knowledge of diabetes domain experts, the structure of the FDO is defined as follows.

Definition 7—Fuzzy Diabetes Ontology (FDO) Ω_{FD}: An FDO Ω_{FD} is a fuzzy ontology Ω_F with the diabetes domain. It contains a fuzzy diabetes layer, fuzzy group relation layer, fuzzy group diabetes layer, fuzzy personal relation layer, and fuzzy personal diabetes layer. ■

Fig. 2 displays the structure for FDO. In the fuzzy diabetes layer, the domain name of FDO is "fuzzy diabetes ontology." The categories are "type-1 diabetes," "type-2 diabetes," "gestational diabetes," and "other specific types of diabetes." Additionally, some fuzzy variables and fuzzy numbers represent the fuzzy concepts, including "Age," "FV_{Age}," "BMI," "FV_{BMI}," "DPF," "FV_{DPF}," "$Glucose$," "$FV_{Glu\cos e}$," "INS," and "FV_{INS}." For instance, the fuzzy concept "Age" has an attribute set $\{FN_{Age}, Value_{Age,}, Mean_{Age}, SD_{Age}, Min_{Age}, Max_{Age}\}$. The fuzzy variable "$Age\ (FV_{Age})$" is derived from the fuzzy concept "Age" and has an attribute set $\{FN_{Age\_Young}, FN_{Age\_Medium}$, and $FN_{Age\_Old}\}$, which represents the knowledge of FV_{Age}. In the fuzzy group relation layer, there are various relations such as $\Re_{\geq FGD_{Age\_30}}$ and $\Re_{\geq FGD_{Age\_40}}$. For instance, $\Re_{\geq FGD_{Age\_40}}$ describes a situation in which an "age greater than 40 years old" relationship exists between the fuzzy concept "Age" in the fuzzy diabetes layer and its specific instances in the fuzzy group diabetes layer. The semantic description of $\Re_{\geq FGD_{Age\_40}}$ can be represented as "slightly old." Similarly, the fuzzy personal relation layer also has some relations like $\Re_{=FPD_{Age\_30}}$ and $\Re_{=FPD_{Age\_40}}$. For instance, $\Re_{=FPD_{Age\_30}}$ represents a situation in which an "age equals about 30" relationship exists between the fuzzy concept "Age" in the fuzzy group diabetes layer and its specific instance FPD_1 in the fuzzy personal diabetes layer. The semantic description of $\Re_{=FPD_{Age\_30}}$ can be represented as "more or less young." Table II lists the examples of semantic descriptions of the constructed fuzzy group relations.

III. FDO-BASED EXPERT SYSTEM FOR DIABETES APPLICATION

This section describes a fuzzy expert system, including a fuzzy ontology, FDO, and SDSA, for diabetes application. The SDSA architecture is introduced first. The knowledge construction mechanism, including a fuzzy concept construction mechanism and a fuzzy relation construction mechanism, is then described.

A. Architecture of the FDO-Based Expert System for Diabetes Application

Fig. 3 illustrates the architecture of the FDO-based expert system for diabetes application. The PIDD is first retrieved from the Internet to become the experimental database. Based on the PIDD, the knowledge construction mechanism constructs the fuzzy concepts by the fuzzy concept construction mechanism and then builds the relationships between the fuzzy concepts by the fuzzy relation construction mechanism. With the fuzzy ontology constructed by the knowledge construction mechanism, the fuzzy diabetes layer of the FDO is then built. Next, the fuzzy group ontology generating mechanism constructs the fuzzy group relations and the fuzzy group diabetes instances. Also, the fuzzy personal ontology generating mechanism executes the construction of the fuzzy personal relations and the fuzzy personal diabetes instances. The FDO is constructed by the knowledge construction mechanism and the fuzzy ontology generating mechanism; it is stored in the

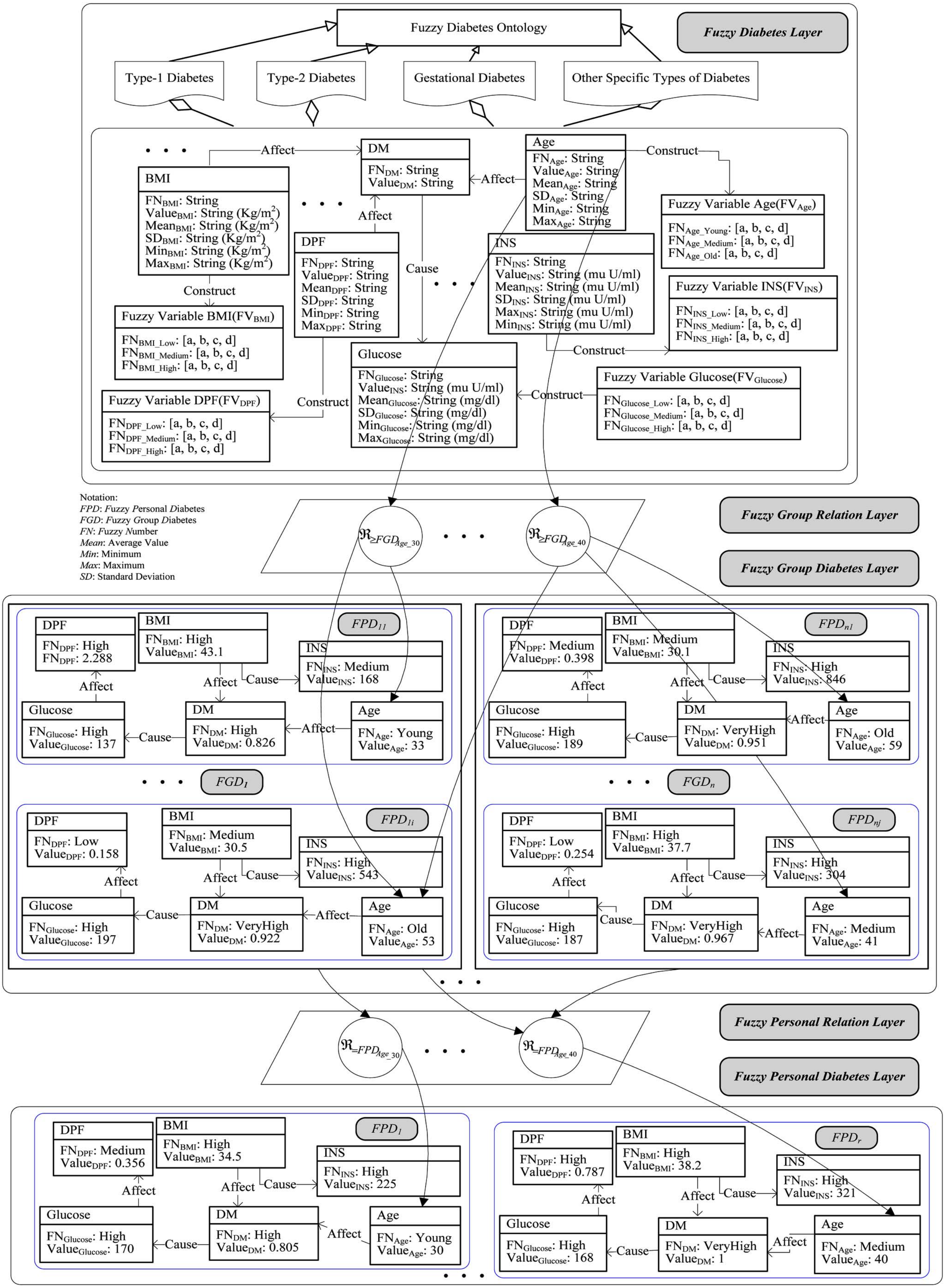

Fig. 2. Structure of the fuzzy diabetes ontology (FDO).

TABLE II
EXAMPLES OF SEMANTIC DESCRIPTIONS OF THE CONSTRUCTED FUZZY GROUP RELATIONS

No	Fuzzy Group Diabetes	Fuzzy Group Relation	Semantic Descriptions
1	$FGD_{\Re_{\geq FGD_{Age\_0}}}$	$\Re_{\geq FGD_{Age\_0}}$	*Very Very Young*
2	$FGD_{\Re_{\geq FGD_{Age\_25}}}$	$\Re_{\geq FGD_{Age\_25}}$	*Very Young*
3	$FGD_{\Re_{\geq FGD_{Age\_30}}}$	$\Re_{\geq FGD_{Age\_30}}$	*More or Less Young*
4	$FGD_{\Re_{\geq FGD_{Age\_35}}}$	$\Re_{\geq FGD_{Age\_35}}$	*Slightly Young*
5	$FGD_{\Re_{\geq FGD_{Age\_40}}}$	$\Re_{\geq FGD_{Age\_40}}$	*Slightly Old*
6	$FGD_{\Re_{\geq FGD_{Age\_45}}}$	$\Re_{\geq FGD_{Age\_45}}$	*More or Less Old*
7	$FGD_{\Re_{\geq FGD_{Age\_50}}}$	$\Re_{\geq FGD_{Age\_50}}$	*Very Old*
8	$FGD_{\Re_{\geq FGD_{Age\_55}}}$	$\Re_{\geq FGD_{Age\_55}}$	*Very Very Old*

FDO repository. Additionally, the diabetes domain experts help to validate and adjust the developed FDO. Next, based on the predefined fuzzy ontology and preconstructed FDO, the semantic fuzzy decision making mechanism executes the fuzzy inference rules to infer the possibility of an individual suffering from diabetes for each instance of FDO. Finally, the diabetes decision support repository stores the inferred semantic descriptions.

B. Fuzzy Concept Construction Mechanism

This subsection describes a fuzzy concept construction mechanism to transfer the information of the PIDD into the required knowledge of the fuzzy diabetes layer of the FDO, which can be denoted by the Web Ontology Language (OWL). OWL is a semantic markup language for publishing and sharing ontologies on the Internet. Table III shows the algorithm of the fuzzy concept construction mechanism. The sketched code, shown in Table IV, is part of the FDO represented by OWL. The OWL specification describes the knowledge of FDO with fuzzy variables and fuzzy numbers.

C. Fuzzy Relation Construction Mechanism

The fuzzy relation construction mechanism is responsible for building the relationships located in the fuzzy group relation layer and the fuzzy personal relation layer for FDO. By using a fuzzy number, the relationships between fuzzy concepts and instances can be expressed to acquire the diabetes domain knowledge. First, the fuzzy numbers must be constructed according to the generated concepts. For the PIDD, each case has nine attributes, listed in Table I, and each attribute can be constructed as a fuzzy variable with some fuzzy numbers. Next, based on the constructed fuzzy concepts, the fuzzy numbers are built by the fuzzy relation construction mechanism; they are stored in the FDO repository. Additionally, an interface is offered for the involved diabetes domain experts to tune and validate the parameters of the built fuzzy numbers. In this paper, a trapezoidal function, as shown in (1), is adopted as the membership function of a fuzzy number and can be expressed as the parameter set $[a, b, c, d]$. Moreover, the relative parameters, a, b, c, and d, denote the *begin support*, *begin core*, *end core*, and *end support* points of the membership function, respectively [11]. With these four parameters, the membership functions of the fuzzy numbers can be plotted automatically and the constructed fuzzy numbers representing an instance-of relation are stored in the FDO repository. Table V shows the algorithm of the fuzzy relation construction mechanism. Table VI shows the default constructed fuzzy numbers.

$$FS(x : a, b, c, d) = \begin{cases} 0 & x < a \\ (x-a)/(b-a) & a \leq x < b \\ 1 & b \leq x \leq c \\ (d-x)/(d-c) & c < x \leq d \\ 0 & x > d. \end{cases} \quad (1)$$

IV. FUZZY ONTOLOGY GENERATION FOR SEMANTIC FUZZY DECISION MAKING

This section introduces the fuzzy ontology generation for semantic fuzzy decision making, which includes a fuzzy group ontology generating mechanism, fuzzy personal ontology generating mechanism, and semantic fuzzy decision making mechanism. Based on the constructed FDO and the predefined fuzzy ontology, the fuzzy group ontology generating mechanism constructs the fuzzy group diabetes instances. However, the fuzzy personal diabetes instances of the FDO are constructed by the fuzzy personal ontology generating mechanism. The semantic fuzzy decision making mechanism then proceeds with the fuzzy inference rules to determine the possibility of an individual suffering from diabetes for all instances of the FDO. Finally, the inferred results are transferred into semantic sentences to simulate the justification of the medical staff; in addition, they are stored in the diabetes decision support repository. Now, these three mechanisms are described briefly as follows.

A. Fuzzy Group Ontology Generating Mechansim

The American Diabetes Association [1] defines diabetes as a disease that affects people of all ages. The incidence of diabetes is even higher in elderly individuals from high-risk populations, such as Native Americans, Hispanics, Asian Americans, and African Americans. This finding implies that age and race significantly impact the risk of developing diabetes. Therefore, the fuzzy concept "Age" is used as a relation factor of the fuzzy group ontology generating mechanism to observe the performance of the proposed approach. Additionally, $\Re_{\geq FGD_{Age\_0}}$, $\Re_{\geq FGD_{Age\_25}}$, $\Re_{\geq FGD_{Age\_30}}$, $\Re_{\geq FGD_{Age\_35}}$, and $\Re_{\geq FGD_{Age\_40}}$ are the constructed fuzzy group relations for diabetes, whose semantic descriptions are referred to as "very very young," "very young," "more or less young," "slightly young," and "slightly old," respectively. Based on the constructed fuzzy group relations, this mechanism builds the instances which associate the relationships with the constructed relation for the fuzzy group diabetes layer. Table VII shows the algorithm of the fuzzy group ontology generating mechanism.

B. Fuzzy Personal Ontology Generating Mechanism

The fuzzy personal ontology generating mechanism focuses mainly on constructing the fuzzy personal diabetes instances based on the constructed fuzzy personal relations. For instance, if four constructed fuzzy personal relations exist, i.e., $\Re_{=FPD_{Age\_25}}$, $\Re_{=FPD_{Age\_30}}$, $\Re_{=FPD_{Age\_35}}$, and $\Re_{=FPD_{Age\_40}}$, then their semantic descriptions are referred to

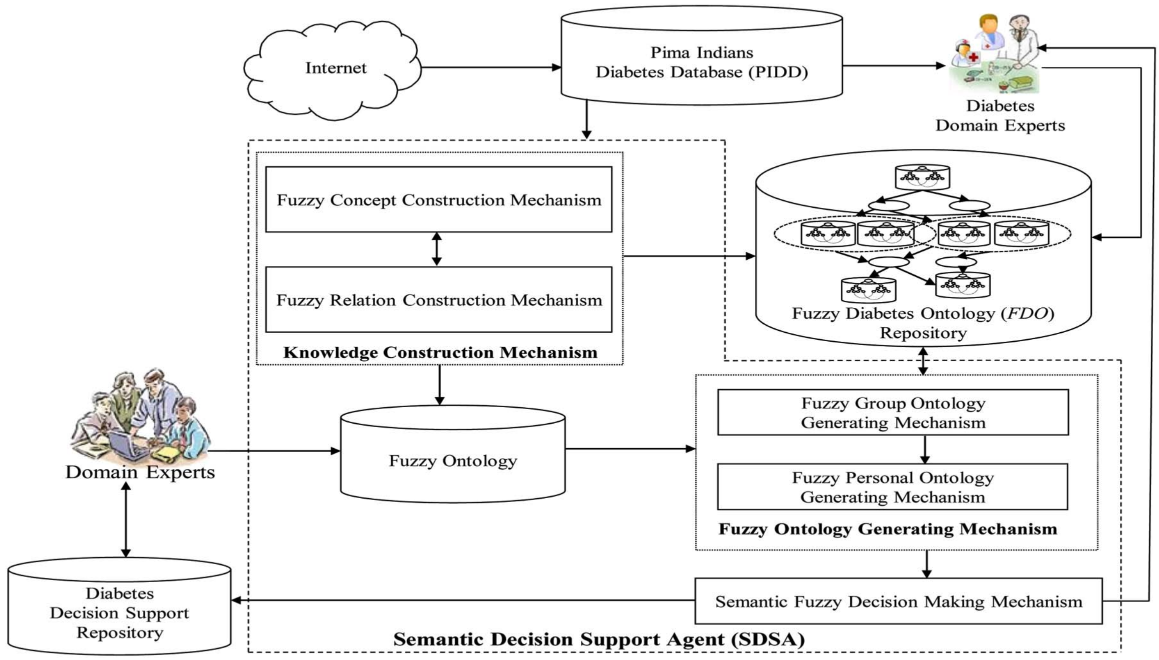

Fig. 3. Architecture of an FDO-based fuzzy expert system for diabetes application.

TABLE III
ALGORITHM OF THE FUZZY CONCEPT CONSTRUCTION MECHANISM

Fuzzy Concept Construction Mechanism Algorithm
BEGIN
1. Input the PIDD with N cases
2. Initialize $i \leftarrow 1$
DO UNTIL ($i > N$)
1) Read out the personal physical data of $case_i$ such as "Number of Times Pregnant (*Pregnant*)," "Plasma Glucose Concentration in a 2-hour OGTT (*Glucose*)," "Diastolic Blood Pressure (*DBP*)," "Triceps Skin Fold Thickness (*TSFT*)," "2-hour Serum Insulin (*INS*)," "Body Mass Index (*BMI*)," "Diabetes Pedigree Function (*DPF*)," "*Age*," and "Diabetes Mellitus (*DM*)" from the PIDD
2) Follow the OWL language to construct the fuzzy concepts of the *FDO* based on the fuzzy variables and fuzzy numbers
3) increment i
END DO UNTIL
END

as "age is around 25 years old," "age is around 30 years old," "age is around 35 years old," and "age is around 40 years old," respectively. The algorithm of the fuzzy personal ontology generating mechanism is similar to one of the fuzzy group ontology generating mechanism listed in Table VII.

C. Semantic Fuzzy Decision Making Mechanism

The semantic fuzzy decision making mechanism separately infers the possibility of an individual developing diabetes for each instance in FDO and transfers the possibility into the form of semantic sentences. According to the American Diabetes Association [1], diabetes is associated with obesity, family history, and age. Additionally, the American Diabetes Association also indicates that the 2-hour OGTT with measurement of plasma glucose and serum insulin concentrations are used as the criteria for diagnosing diabetes. Consequently, five attributes, i.e., $Glucose$, INS, BMI, DPF, and Age, are selected as the input fuzzy variables of the adopted fuzzy rule-based inference system; in addition, the related information about fuzzy numbers is stored in the ontology. Tuned and validated by the diabetes domain experts, the parameters of the fuzzy numbers are listed in Table VIII.

The fuzzy variable $Glucose$ has three fuzzy numbers, i.e., $Glucose\_Low$, $Glucose\_Medium$, and $Glucose\_High$. For the fuzzy variable INS, fuzzy concepts and knowledge of the 2-hour serum insulin are expressed in human communication by using the fuzzy numbers INS_Low, INS_Medium, and INS_High. The membership functions of BMI also have three fuzzy numbers, i.e., BMI_Low, BMI_Medium, and BMI_High. The fuzzy numbers DPF_Low, DPF_Medium, and DPF_High are defined for the fuzzy variable DPF. The membership functions of the fuzzy variable Age are Age_Young, Age_Medium, and Age_Old. The five fuzzy numbers, i.e., $DM\_VeryLow$, DM_Low, DM_Medium, DM_High, and $DM\_VeryHigh$, are adopted to represent the possibility of this instance with diabetes for output fuzzy variable DM. Hence, there are totally 234 fuzzy inference rules utilized in this paper.

The proposed fuzzy rule-based inference system for the semantic fuzzy decision making mechanism consists of four steps, i.e., fuzzy matching, fuzzy inference, combination,

TABLE IV
PART OF FUZZY DIABETES ONTOLOGY (*FDO*) REPRESENTED BY OWL

```xml
<?xml version="1.0"?>
…
<rdf:RDF xmlns="http://www.owl-ontologies.com/DiabetesOntology.owl#"
  …
  <owl:Class rdf:ID="Age">
    <rdfs:subClassOf rdf:resource="#Type-2_Diabetes"/>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Construct"/>
        <owl:allValuesFrom rdf:resource="#Fuzzy_Variable_Age"/>
      </owl:Restriction>
    </rdfs:subClassOf>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Affect"/>
        <owl:allValuesFrom rdf:resource="#DM"/>
      </owl:Restriction>
    </rdfs:subClassOf>
  </owl:Class>
  <owl:Class rdf:ID="BMI">
    <rdfs:subClassOf rdf:resource="#Type-2_Diabetes"/>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Construct"/>
        <owl:allValuesFrom rdf:resource="#Fuzzy_Variable_BMI"/>
      </owl:Restriction>
    </rdfs:subClassOf>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Affect"/>
        <owl:allValuesFrom rdf:resource="#DM"/>
      </owl:Restriction>
    </rdfs:subClassOf>
  </owl:Class>
  <owl:ObjectProperty rdf:ID="Cause">
    <rdf:type rdf:resource="&owl;TransitiveProperty"/>
  </owl:ObjectProperty>
  <owl:ObjectProperty rdf:ID="Construct"/>
<owl:Class rdf:ID="DM">
    <rdfs:subClassOf rdf:resource="#Type-2_Diabetes"/>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Cause"/>
        <owl:allValuesFrom rdf:resource="#Glucose"/>
      </owl:Restriction>
    </rdfs:subClassOf>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Cause"/>
        <owl:allValuesFrom rdf:resource="#INS"/>
      </owl:Restriction>
    </rdfs:subClassOf>
  </owl:Class>
 <owl:Class rdf:ID="DPF">
    <rdfs:subClassOf rdf:resource="#Type-2_Diabetes"/>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Affect"/>
        <owl:allValuesFrom rdf:resource="#DM"/>
      </owl:Restriction>
    </rdfs:subClassOf>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Construct"/>
        <owl:allValuesFrom rdf:resource="#Fuzzy_Variable_DPF"/>
      </owl:Restriction>
    </rdfs:subClassOf>
  </owl:Class>
  …
<owl:Class rdf:ID="Glucose">
    <rdfs:subClassOf rdf:resource="#Type-2_Diabetes"/>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Construct"/>
        <owl:allValuesFrom rdf:resource="#Fuzzy_Variable_Glucose"/>
      </owl:Restriction>
    </rdfs:subClassOf>
  </owl:Class>
  <owl:Class rdf:ID="INS">
    <rdfs:subClassOf rdf:resource="#Type-2_Diabetes"/>
    <rdfs:subClassOf>
      <owl:Restriction>
        <owl:onProperty rdf:resource="#Construct"/>
        <owl:allValuesFrom rdf:resource="#Fuzzy_Variable_INS"/>
      </owl:Restriction>
    </rdfs:subClassOf>
  </owl:Class>
…
 </rdf:RDF>
```

and defuzzification [11]. First, the membership degrees for all instances of the FDO are calculated using the membership functions and then using the AND fuzzy conjunction, the operator combines the matching degree of each rule with multiple conditions. Second, the fuzzy inference is invoked to produce their inferred conclusions by using the clipping method. Third, the inference results of the rules fired the same consequences are integrated by performing MAX fuzzy disjunction operations. Fourth, the final combined fuzzy conclusion is converted into a crisp value by using the centroid method. However, in order to range the possibility of the instance with diabetes from 0 to 1, a normalizing function S [12] is adopted in this paper and calculated by

$$S(x:m_1,m_2)=\begin{cases}0 & x<m_1\\ 2\left(\frac{x-m_1}{m_2-m_1}\right)^2 & m_1\le x\le \frac{m_1+m_2}{2}\\ 1-2\left(\frac{x-m_2}{m_2-m_1}\right)^2 & \frac{m_1+m_2}{2}\le x<m_2\\ 1 & x\ge m_2.\end{cases} \tag{2}$$

Finally, the proposed SDSA analyzes the personal physical data, converts the inferred results into knowledge, and then presents the decision results through semantic descriptions [29], [30]. Table IX displays the patterns of the semantic sentence of the output semantic descriptions, including a semantic analysis sentence and a semantic decision sentence. Table X shows the algorithm of the semantic fuzzy decision making mechanism.

V. Experimental Results

The proposed FDO-based fuzzy expert system for diabetes application was implemented with the C++ Builder 2007 programming language. The experimental environment was constructed to evaluate the performance of the proposed approach; in addition, PIDD was chosen as the evaluated data set. The proposed approach can analyze the personal physical data of the PIDD and generate corresponding human knowledge based on the FDO. The first experiment shows seven sets of semantic results in Table XI(a)–(g), indicating that the proposed approach automatically supports the analysis of the physical data. The

TABLE V
ALGORITHM OF THE FUZZY RELATION CONSTRUCTION MECHANISM

Fuzzy Relation Construction Mechanism Algorithm
BEGIN

1. Input the PIDD with N cases
2. Initialize $i \leftarrow 1$
3. Initialize $Sum_{Pregnant} \leftarrow 0$
4. Initialize $Sum_{Glucose} \leftarrow 0$
5. Initialize $Sum_{DBP} \leftarrow 0$
6. Initialize $Sum_{TSFT} \leftarrow 0$
7. Initialize $Sum_{INS} \leftarrow 0$
8. Initialize $Sum_{BMI} \leftarrow 0$
9. Initialize $Sum_{DPF} \leftarrow 0$
10. Initialize $Sum_{Age} \leftarrow 0$

Step1. Sum the values of all attributes of *N* cases except for the attribute "Diabetes Mellitus (*DM*)"

DO UNTIL ($i > N$)

1) Extract the values of "Number of Times Pregnant (*Pregnant*)," "Plasma Glucose Concentration in a 2-hour OGTT (*Glucose*)," "Diastolic Blood Pressure (*DBP*)," "Triceps Skin Fold Thickness (*TSFT*)," "2-hour Serum Insulin (*INS*)," "Body Mass Index (*BMI*)," "Diabetes Pedigree Function (*DPF*)," and "*Age*," from the PIDD for $case_i$

2) $Sum_{Pregnant} \mathrel{+}= Value_{Pregnant_i}$

3) $Sum_{Glucose} \mathrel{+}= Value_{Glucose_i}$

4) $Sum_{DBP} \mathrel{+}= Value_{DBP_i}$

5) $Sum_{TSFT} \mathrel{+}= Value_{TSFT_i}$

6) $Sum_{INS} \mathrel{+}= Value_{INS_i}$

7) $Sum_{BMI} \mathrel{+}= Value_{BMI_i}$

8) $Sum_{DPF} \mathrel{+}= Value_{DPF_i}$

9) $Sum_{Age} \mathrel{+}= Value_{Age_i}$

10) increment i

END DO UNTIL

Step2. Calculate the values of mean and standard deviation of the extracted attributes.

1) Calculate the mean value : $Mean_{Pregnant}$, $Mean_{Glucose}$, $Mean_{DBP}$, $Mean_{TSFT}$, $Mean_{INS}$, $Mean_{BMI}$, $Mean_{DPF}$, and $Mean_{Age}$, by

$$\frac{Sum_{Pregnant}}{N}, \frac{Sum_{Glucose}}{N}, \frac{Sum_{DBP}}{N}, \frac{Sum_{TSFT}}{N}, \frac{Sum_{INS}}{N}, \frac{Sum_{BMI}}{N}, \frac{Sum_{DPF}}{N}, \text{ and } \frac{Sum_{Age}}{N}, \text{ respectively}$$

2) Calculate the standard deviation: $SD_{Pregnant}$, $SD_{Glucose}$, SD_{DBP}, SD_{TSFT}, SD_{INS}, SD_{BMI}, SD_{DPF}, and SD_{Age}, by

$$\sqrt{\frac{\sum_{i=1}^{N}(Value_{Pregnant_i} - Mean_{Pregant})^2}{N}}, \sqrt{\frac{\sum_{i=1}^{N}(Value_{Glucose_i} - Mean_{Glucose})^2}{N}}, \sqrt{\frac{\sum_{i=1}^{N}(Value_{DBP_i} - Mean_{DBP})^2}{N}}$$

$$\sqrt{\frac{\sum_{i=1}^{N}(Value_{TSFT_i} - Mean_{TSFT})^2}{N}}, \sqrt{\frac{\sum_{i=1}^{N}(Value_{INS_i} - Mean_{INS})^2}{N}}, \sqrt{\frac{\sum_{i=1}^{N}(Value_{BMI_i} - Mean_{BMI})^2}{N}}$$

$$\sqrt{\frac{\sum_{i=1}^{N}(Value_{DPF_i} - Mean_{DPF})^2}{N}}, \text{ and } \sqrt{\frac{\sum_{i=1}^{N}(Value_{Age_i} - Mean_{Age})^2}{N}}, \text{ respectively}$$

3) Sort all of $Value_{Pregnant_i}$, $Value_{Glucose_i}$, $Value_{DBP_i}$, $Value_{TSFT_i}$, $Value_{INS_i}$, $Value_{BMI_i}$, $Value_{DPF_i}$, and $Value_{Age_i}$ in an ascending order to get the $Min_{Pregnant}$, $Min_{Glucose}$, Min_{DBP}, Min_{TSFT}, Min_{INS}, Min_{BMI}, Min_{DPF}, Min_{Age}, $Max_{Pregnant}$, $Max_{Glucose}$, Max_{DBP}, Max_{TSFT}, Max_{INS}, Max_{BMI}, Max_{DPF}, and Max_{Age}

4) Construct the default fuzzy numbers as listed in Table VI

5) Using the constructed fuzzy numbers, build the fuzzy relations that describe an *instance-of* relation between the fuzzy concepts and its specific instances

6) Store the mean value, standard deviation value, minimum value, and maximum value to the *FDO* repository

7) Store the default constructed fuzzy numbers to the *FDO* repository

END

acquired information is then transferred into knowledge, and finally the proposed method presents them in the form of the semantic descriptions of humans. Table XI(a) is considered as an example. For case 4, the personal physical data for $Glucose$, INS, BMI, DPF, and Age are 89 mg/dl, 94 mu U/ml, 28.1 kg/m^2, 0.167, and 21, respectively. The proposed SDSA suggests that the possibility of developing diabetes is "very low," which matches with the justification of the medical staff, "The person is non-diabetic." Table XI(b)–(e) also indicate that SDSA suggests similar justifications to the ones that the medical staff made for cases 19, 21, 5, and 9, respectively. For case 7, based on the physical data of an individual as listed in Table XI(f), the proposed SDSA suggests that the possibility of developing diabetes is "very low," which does not match with the justification of the medical staff, "The person is diabetic." For case 1, as listed in Table XI(g), owing to the condition

TABLE VI
DEFAULT CONSTRUCTED FUZZY NUMBERS

Fuzzy Variable	Fuzzy Number	[*a*, *b*, *c*, *d*]
Pregnant	*Pregnant_Low*	$[Min_{Pregnant}, Min_{Pregnant}, Mean_{Pregnant} - SD_{Pregnant}, Mean_{Pregnant}]$
	Pregnant_Medium	$[Mean_{Pregnant} - SD_{Pregnant}, Mean_{Pregnant}, Mean_{Pregnant}, Mean_{Pregnant} + SD_{Pregnant}]$
	Pregnant_High	$[Mean_{Pregnant}, Mean_{Pregnant} + SD_{Pregnant}, Max_{Pregnant}, Max_{Pregnant}]$
Glucose	*Glucose_Low*	$[Min_{Glucose}, Min_{Glucose}, Mean_{Glucose} - SD_{Glucose}, Mean_{Glucose}]$
	Glucose_Medium	$[Mean_{Glucose} - SD_{Glucose}, Mean_{Glucose}, Mean_{Glucose}, Mean_{Glucose} + SD_{Glucose}]$
	Glucose_High	$[Mean_{Glucose}, Mean_{Glucose} + SD_{Glucose}, Max_{Glucose}, Max_{Glucose}]$
DBP	*DBP_Low*	$[Min_{DBP}, Min_{DBP}, Mean_{DBP} - SD_{DBP}, Mean_{DBP}]$
	DBP_Medium	$[Mean_{DBP} - SD_{DBP}, Mean_{DBP}, Mean_{DBP}, Mean_{DBP} + SD_{DBP}]$
	DBP_High	$[Mean_{DBP}, Mean_{DBP} + SD_{DBP}, Max_{DBP}, Max_{DBP}]$
TSFT	*TSFT_Low*	$[Min_{TSFT}, Min_{TSFT}, Mean_{TSFT} - SD_{TSFT}, Mean_{TSFT}]$
	TSFT_Medium	$[Mean_{TSFT} - SD_{TSFT}, Mean_{TSFT}, Mean_{TSFT}, Mean_{TSFT} + SD_{TSFT}]$
	TSFT_High	$[Mean_{TSFT}, Mean_{TSFT} + SD_{TSFT}, Max_{TSFT}, Max_{TSFT}]$
INS	*INS_Low*	$[Min_{INS}, Min_{INS}, Mean_{INS} - SD_{INS}, Mean_{INS}]$
	INS_Medium	$[Mean_{INS} - SD_{INS}, Mean_{INS}, Mean_{INS}, Mean_{INS} + SD_{INS}]$
	INS_High	$[Mean_{INS}, Mean_{INS} + SD_{INS}, Max_{INS}, Max_{INS}]$
BMI	*BMI_Low*	$[Min_{BMI}, Min_{BMI}, Mean_{BMI} - SD_{BMI}, Mean_{BMI}]$
	BMI_Medium	$[Mean_{BMI} - SD_{BMI}, Mean_{BMI}, Mean_{BMI}, Mean_{BMI} + SD_{BMI}]$
	BMI_High	$[Mean_{BMI}, Mean_{BMI} + SD_{BMI}, Max_{BMI}, Max_{BMI}]$
DPF	*DPF_Low*	$[Min_{DPF}, Min_{DPF}, Mean_{DPF} - SD_{DPF}, Mean_{DPF}]$
	DPF_Medium	$[Mean_{DPF} - SD_{DPF}, Mean_{DPF}, Mean_{DPF}, Mean_{DPF} + SD_{DPF}]$
	DPF_High	$[Mean_{DPF}, Mean_{DPF} + SD_{DPF}, Max_{DPF}, Max_{DPF}]$
Age	*Age_Young*	$[Min_{Age}, Min_{Age}, Mean_{Age} - SD_{Age}, Mean_{Age}]$
	Age_Medium	$[Mean_{Age} - SD_{Age}, Mean_{Age}, Mean_{Age}, Mean_{Age} + SD_{Age}]$
	Age_Old	$[Mean_{Age}, Mean_{Age} + SD_{Age}, Max_{Age}, Max_{Age}]$

TABLE VII
ALGORITHM OF THE FUZZY GROUP ONTOLOGY GENERATING MECHANISM

Fuzzy Group Ontology Generating Mechanism Algorithm

BEGIN

1. Input the *FDO* with *N* instances.
2. Initialize the *fuzzy group diabetes instance* set $FGD_{\Re_{\geq FGD_{Age\_0}}} \leftarrow \phi$
3. Initialize the *fuzzy group diabetes instance* set $FGD_{\Re_{\geq FGD_{Age\_25}}} \leftarrow \phi$
4. Initialize the *fuzzy group diabetes instance* set $FGD_{\Re_{\geq FGD_{Age\_30}}} \leftarrow \phi$
5. Initialize the *fuzzy group diabetes instance* set $FGD_{\Re_{\geq FGD_{Age\_35}}} \leftarrow \phi$
6. Initialize the *fuzzy group diabetes instance* set $FGD_{\Re_{\geq FGD_{Age\_40}}} \leftarrow \phi$
7. Initialize $i \leftarrow 1$

DO UNTIL ($i > N$)

1) Read out the semantic description of the attribute FN_{Age_i} from the attribute set of the $instance_i$

2) Read out the semantic description of the attribute FN_{DM_i} from the attribute set of the $instance_i$

3) **IF** (FN_{Age_i} is *Very Very Young*) **AND** (FN_{DM_i} is *Very High*) **THEN**

Add $instance_i$ to $FGD_{\Re_{\geq FGD_{Age\_0}}}$

END IF

4) **IF** (FN_{Age_i} is *Very Young*) **AND** (FN_{DM_i} is *Very High*) **THEN**

Add $instance_i$ to $FGD_{\Re_{\geq FGD_{Age\_25}}}$

END IF

5) **IF** (FN_{Age_i} is *More or Less Young*) **AND** (FN_{DM_i} is *Very High*) **THEN**

Add $instance_i$ to $FGD_{\Re_{\geq FGD_{Age\_30}}}$

END IF

6) **IF** (FN_{Age_i} is *Slightly Young*) **AND** (FN_{DM_i} is *Very High*) **THEN**

Add $instance_i$ to $FGD_{\Re_{\geq FGD_{Age\_35}}}$

END IF

7) **IF** (FN_{Age_i} is *Slightly Old*) **AND** (FN_{DM_i} is *Very High*) **THEN**

Add $instance_i$ to $FGD_{\Re_{\geq FGD_{Age\_40}}}$

END IF

8) increment *i*

END DO UNTIL

END

TABLE VIII
PARAMETERS OF TRAPEZOIDAL MEMBERSHIP FUNCTIONS

Fuzzy Number	Fuzzy Number	[*a*, *b*, *c*, *d*]
Glucose	*Glucose_Low*	[56, 56, 100, 125]
	Glucose_Medium	[92, 125, 125, 152]
	Glucose_High	[125, 145, 198, 198]
INS	*INS_Low*	[14, 14, 90, 140]
	INS_Medium	[90, 140, 140, 274]
	INS_High	[140, 274, 846, 846]
BMI	*BMI_Low*	[18, 18, 22, 28]
	BMI_Medium	[22, 28, 28, 36]
	BMI_High	[28, 36.6, 67, 67]
DPF	*DPF_Low*	[0.085, 0.085, 0.15, 0.35]
	DPF_Medium	[0.15, 0.48, 0.48, 0.8]
	DPF_High	[0.7, 0.8, 2.4, 2.4]
Age	*Age_Young*	[20, 20, 30, 38]
	Age_Medium	[30, 38, 38, 45]
	Age_Old	[38, 45, 81, 81]
DM	*DM_VeryLow*	[0, 0, 0.1, 0.2]
	DM_Low	[0.1, 0.2, 0.3, 0.4]
	DM_Medium	[0.3, 0.4, 0.6, 0.7]
	DM_High	[0.6, 0.7, 0.8, 0.9]
	DM_VeryHigh	[0.8, 0.9, 1, 1]

that INS is impossible to equal "0" for a normal individual, the SDSA detects that the physical data of the individual is unreasonable and generates the semantic descriptions of "The personal physical data may be wrong."

The second experiment evaluates the performance of the SDSA based on how the SDSA and the medical staff differ in results for various threshold values. Some metrics, including accuracy, precision, and recall, are utilized as the criteria to perform this experiment. The true positive (TP) and the true negative (TN) denote the correct classification. However, a false positive (FP) is when the outcome is not accurately predicted as yes (or positive); however, it is no (or negative). Still, a false negative (FN) is when the outcome is not accurately predicted as no (or negative); however, it is yes (positive). Table XII lists the various outcomes of a two-class prediction [20]. Accuracy is the proportion of the total number of predictions that were correct. The precision is the proportion of the predicted positive cases that were correct. Recall is the proportion of the negative cases that were correctly identified. True negative rate evaluates the proportion of negatives that are correctly identified. Equations (3)–(6) show the formulas for the accuracy, precision, recall, and true negative rate, respectively

$$Accuracy = \frac{TN+TP}{TN+FP+FN+TP} \times 100\% \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (4)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (5)$$

$$True\ Negative\ Rate = \frac{TN}{TN+FP} \times 100\%. \quad (6)$$

Table XIII lists the values of accuracy, precision, recall, and true negative rate under various thresholds based on the fuzzy group diabetes. According to this table, the accuracy is gradually raised with the age of the diabetics being older when the threshold value is fixed. This table also indicates the following tendency: a lower precision implies a higher recall. Meanwhile, according to Table XIII, the accuracy becomes higher if the screening age is done for the cases with diabetes. The final experiment compares the accuracy of the proposed method with results of studies involving the PIDD [4], [5], [8]. Comparing these methods, as listed in Table XIV, reveals that the proposed method achieves the first two highest accuracy values for "slightly old" and "slightly young" FGD relations.

VI. CONCLUSIONS AND DISCUSSIONS

This paper has presented a novel five-layer fuzzy ontology to model the domain knowledge with uncertainty and extend the fuzzy ontology to the diabetes domain. Additionally, an SDSA is also developed for semantic decision making in diagnosing diabetes. The experimental data set, PIDD, is initially processed by the knowledge construction mechanism to construct the fuzzy concepts and fuzzy relations of the FDO. The required knowledge for the proposed agent is then stored in the FDO repository. The fuzzy ontology generating mechanism generates instances of the FDO to associate the relation layer with concepts in the fuzzy group diabetes layer and the fuzzy personal diabetes layer using fuzzy numbers. The semantic fuzzy decision making mechanism then executes the fuzzy inference rules to make a decision on the possibility of individuals suffering from diabetes and to present the knowledge with semantic descriptions. Finally, the results are stored in the diabetes decision support repository. Experimental results indicate that the proposed method can analyze data and further transfer the acquired information into the knowledge to simulate the thinking process of humans. Our results further demonstrate that the proposed method works more effectively for diabetes application than previously developed ones. Despite its contributions, this study has certain limitations, which points toward the following areas of future research:

- While this paper has developed a fuzzy expert system for diagnosing diabetes, the results have been discussed in the context of only one data set. Hence, developing a similar model for another data set or another domain, constructing the similar fuzzy ontology, including the fuzzy concepts and fuzzy numbers, as well as modifying the fuzzy inference rules through domain experts or related machine learning mechanisms, are our future works.
- Although the proposed fuzzy ontology can model the domain knowledge of diabetes, the fuzzification approach applied in the fuzzy expert system is still more important rather than the ontology model used herein.
- Improvement in the performance is largely owed to the feature space characterizations of the chosen data set rather than the reasoning mechanism. The reasoning mechanism based on the feature space characterizations is a fuzzy rule-based system, which contains 234 fuzzy inference rules in the fuzzy expert system.

TABLE IX
SEMANTIC SENTENCES' PATTERNS OF THE OUTPUT SEMANTIC DESCRIPTIONS

Semantic Analysis Sentence (SAS):

The personal physical data exhibit that the person is at **[*FN_{Age}*: *Young, Medium, Old*]** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **[*$FN_{Glucose}$*: *Low, Medium, High*]**, *2-hour serum insulin is* **[*FN_{INS}*: *Low, Medium, High*]**, *body mass index is* **[*FN_{BMI}*: *Low, Medium, High*]**, *and diabetes pedigree function is* **[*FN_{DPF}*: *Low, Medium, High*]**.

Semantic Decision Sentence (SDS):

The SDSA justifies that the possibility of suffering from diabetes for this person is **[*FN_{DM}*: *VeryLow, Low, Medium, High, VeryHigh*]** (Possibility: **[0, 1]**).

TABLE X
ALGORITHM OF THE SEMANTIC FUZZY DECISION MAKING MECHANISM

Fuzzy Inference for Semantic Fuzzy Decision Making Mechanism Algorithm
BEGIN
1. Input the *FDO* with *N* instances
2. Input fuzzy set A_{in} ={*Glucose_Low*, *Glucose_Medium*, *Glucose_High*, *INS_Low*, *INS_Medium*, *INS_High*, *BMI_Low*, *BMI_Medium*, *BMI_High*, *DPF_Low*, *DPF_Medium*, *DPF_High*, *Age_Young*, *Age_Medium*, *Age_Old*}
3. Output fuzzy set A_{out} ={*DM_VeryLow*, *DM_Low*, *DM_Medium*, *DM_High*, *DM_VeryHigh*}
4. Input fuzzy inference rules set *FIR* = {*Rule1*, *Rule2*, …, *Rule K*}
5. Initialize the plasma glucose concentration in a 2-hour OGTT set $Set_{Glucose} \leftarrow \phi$
6. Initialize the 2-hour serum insulin set $Set_{INS} \leftarrow \phi$
7. Initialize the body mass index set $Set_{BMI} \leftarrow \phi$
8. Initialize the diabetes pedigree function set $Set_{DPF} \leftarrow \phi$
9. Initialize the age set $Set_{Age} \leftarrow \phi$
10. Initialize the diabetes mellitus set $Set_{DM} \leftarrow \phi$
11. Initialize $i \leftarrow 1$

Step1: Read the value of each attribute of each instance.
DO UNTIL ($i > N$)
1) Read out the attribute $Value_{Glucose_i}$ of the fuzzy concept "*Glucose*", then add $Value_{Glucose_i}$ to $Set_{Glucose}$
2) Read out the attribute $Value_{INS_i}$ of the fuzzy concept "*INS*", then add $Value_{INS_i}$ to Set_{INS}
3) Read out the attribute $Value_{BMI_i}$ of the fuzzy concept "*BMI*", then add $Value_{BMI_i}$ to Set_{BMI}
4) Read out the attribute $Value_{DPF_i}$ of the fuzzy concept "*DPF*", then add $Value_{DPF_i}$ to Set_{DPF}
5) Read out the attribute $Value_{Age_i}$ of the fuzzy concept "*Age*", then add $Value_{Age_i}$ to Set_{Age}
6) increment *i*

END DO UNTIL
Initialize $i \leftarrow 1$

Step2: Execute the fuzzy inference
DO UNTIL ($i > N$)
1. Let $X_i \leftarrow [(Value_{Glucose_i}, Value_{INS_i}, Value_{BMI_i}, Value_{DPF_i}, Value_{Age_i})]$
2. Initialize $k \leftarrow 1$

Step2.1: Calculate the matching degree and center of area of each rule
DO UNTIL ($k > K$)
1) Calculate the matching degree of the *Rule k* by $\mu_{i\_k} \leftarrow MIN(\mu_{A_{in}}(X_i))$
2) Calculate the center of area of the *Rule k* by $y_{A_{out}i\_k} \leftarrow COA(\mu_{i\_k})$
3) increment *k*

END DO UNTIL
Initialize $p \leftarrow 1$

Step2.2: Calculate the aggregation of the fired rules having the same consequences
DO UNTIL ($p > P$)
1) Calculate the membership values of X_i to the fuzzy classes F_{i_p} by $y_{i\_p} \leftarrow MAX(y_{A_{out}i\_k})$
where F_{i_p} means the fuzzy class for all of fuzzy rules. Each fuzzy class is an aggregation of the fired rules that have the same consequences
2) increment *p*

END DO UNTIL
3. Defuzzify into a crisp value by $$DM_i \leftarrow \frac{\sum_{p=1}^{P} w_{i\_p} y_{i\_p}}{\sum_{p=1}^{P} w_{i\_p}}$$
where w_{i_p} means the weight for y_{i_p} and *P* means the number of fuzzy numbers of the output fuzzy variables, *DM*
4. Add DM_i to Set_{DM}
5. increment *i*

END DO UNTIL

Step3: Sort and smooth the Set_{DM}
1. Sort the DM set Set_{DM} in an ascending order
2. Set the minimum value of Set_{DM} to the value of "m_1" of Eq. (2)
3. Set the maximum value of Set_{DM} to the value of "m_2" of Eq. (2)
4. Smooth the Set_{DM} by Eq. (2) and store the results back to Set_{DM}
5. Store the possibility of developing diabetes of each instance of the *FDO* to the diabetes decision support repository

TABLE X
(Continued.) ALGORITHM OF THE SEMANTIC FUZZY DECISION MAKING MECHANISM

Step4: Convert the inference results into knowledge and present them in the semantic sentences
Initialize $i \leftarrow 1$
DO UNTIL $(i > N)$
Step4.1: Check the value of $Value_{Glucose_i}$, $Value_{INS_i}$, $Value_{BMI_i}$, $Value_{DPF_i}$, **and** $Value_{Age_i}$
IF $Value_{Glucose_i} > 0$ and $Value_{INS_i} > 0$ and $Value_{BMI_i} > 0$ and $Value_{DPF_i} > 0$ and $Value_{Age_i} > 0$ **THEN**
Step4.1.1: Find the fuzzy numbers with the maximum membership degree for $Value_{Glucose_i}$, $Value_{INS_i}$, $Value_{BMI_i}$, $Value_{DPF_i}$, **and** $Value_{Age_i}$
1) $\mu_{Glucose_i} \leftarrow MAX(\mu_{Glucose\_Low}(Value_{Glucose_i}), \mu_{Glucose\_Medium}(Value_{Glucose_i}), \mu_{Glucose\_High}(Value_{Glucose_i}))$
IF $\mu_{Glucose_i} = \mu_{Glucose\_Low}(Value_{Glucose_i})$ **THEN** $FN_{Glucose_i} \leftarrow Glucose\_Low$
ELSE IF $\mu_{Glucose_i} = \mu_{Glucose\_Medium}(Value_{Glucose_i})$ $FN_{Glucose_i} \leftarrow Glucose\_Medium$
ELSE $FN_{Glucose_i} \leftarrow Glucose\_High$
END IF
2) $\mu_{INS_i} \leftarrow MAX(\mu_{INS\_Low}(Value_{INS_i}), \mu_{INS\_Medium}(Value_{INS_i}), \mu_{INS\_High}(Value_{INS_i}))$
IF $\mu_{INS_i} = \mu_{INS\_Low}(Value_{INS_i})$ **THEN** $FN_{INS_i} \leftarrow INS\_Low$
ELSE IF $\mu_{INS_i} = \mu_{INS\_Medium}(Value_{INS_i})$ $FN_{INS_i} \leftarrow INS\_Medium$
ELSE $FN_{INS_i} \leftarrow INS\_High$
END IF
3) $\mu_{BMI_i} \leftarrow MAX(\mu_{BMI\_Low}(Value_{BMI_i}), \mu_{BMI\_Medium}(Value_{BMI_i}), \mu_{BMI\_High}(Value_{BMI_i}))$
IF $\mu_{BMI_i} = \mu_{BMI\_Low}(Value_{BMI_i})$ **THEN** $FN_{BMI_i} \leftarrow BMI\_Low$
ELSE IF $\mu_{BMI_i} = \mu_{BMI\_Medium}(Value_{BMI_i})$ $FN_{BMI_i} \leftarrow BMI\_Medium$
ELSE $FN_{BMI_i} \leftarrow BMI\_High$
END IF
4) $\mu_{DPF_i} \leftarrow MAX(\mu_{DPF\_Low}(Value_{DPF_i}), \mu_{DPF\_Medium}(Value_{DPF_i}), \mu_{DPF\_High}(Value_{DPF_i}))$
IF $\mu_{DPF_i} = \mu_{DPF\_Low}(Value_{DPF_i})$ **THEN** $FN_{DPF_i} \leftarrow DPF\_Low$
ELSE IF $\mu_{DPF_i} = \mu_{DPF\_Medium}(Value_{DPF_i})$ $FN_{DPF_i} \leftarrow DPF\_Medium$
ELSE $FN_{DPF_i} \leftarrow DPF\_High$
END IF
5) $\mu_{Age_i} \leftarrow MAX(\mu_{Age\_Young}(Value_{Age_i}), \mu_{Age\_Medium}(Value_{Age_i}), \mu_{Age\_Old}(Value_{Age_i}))$
IF $\mu_{Age_i} = \mu_{Age\_Young}(Value_{Age_i})$ **THEN** $FN_{Age_i} \leftarrow Age\_Young$
ELSE IF $\mu_{Age_i} = \mu_{Age\_Medium}(Value_{Age_i})$ $FN_{Age_i} \leftarrow Age\_Medium$
ELSE $FN_{Age_i} \leftarrow Age\_Old$
END IF
Step 4.1.2: Find the fuzzy numbers with the maximum membership degree for DM_i
$\mu_{DM_i} \leftarrow MAX(\mu_{DM\_VeryLow}(DM_i), \mu_{DM\_Low}(DM_i), \mu_{DM\_Medium}(DM_i), \mu_{DM\_High}(DM_i), \mu_{DM\_VeryHigh}(DM_i))$
IF $\mu_{DM_i} = \mu_{DM\_VeryLow}(DM_i)$ **THEN** $FN_{DM_i} \leftarrow DM\_VeryLow$
ELSE IF $\mu_{DM_i} = \mu_{DM\_Low}(DM_i)$ **THEN** $FN_{DM_i} \leftarrow DM\_Low$
ELSE IF $\mu_{DM_i} = \mu_{DM\_Medium}(DM_i)$ $FN_{DM_i} \leftarrow DM\_Medium$
ELSE IF $\mu_{DM_i} = \mu_{DM\_High}(DM_i)$ $FN_{DM_i} \leftarrow DM\_High$
ELSE $FN_{DM_i} \leftarrow DM\_VeryHigh$
END IF
Step4.1.3: Present the knowledge in the form of the human nature language
This personal physical data exhibit that the person is at FN_{Age_i} age, meanwhile the plasma glucose concentration in 2-hour OGTT is $FN_{Glucose_i}$, 2-hour serum insulin is FN_{INS_i} , body mass index is FN_{BMI_i} , and diabetes pedigree function is FN_{DPF_i} .
The *SDSA* justifies that the possibility of suffering from diabetes for this person is FN_{DM_i} . (Possibility: DM_i).
ELSE
The SDSA justifies that the personal physical data may be wrong.
END IF
Step4.2: increment i
END DO UNTIL
END

Future works should test the fuzzification approach used herein for other similar tasks or diabetes-related data sets to evaluate its capability to produce a similar accuracy.

- Future works should explore the proposed fuzzy expert system with respect to increasing the acceptability of the system in other domain and should also examine the accuracy of the fuzzy expert system in predicting diabetes cases from another data set similarly encoded.
- Among the other relevant issues that should be further considered is when the data set is changed, which includes modifying the rules of the fuzzy expert system to perform with a similar accuracy as that of the Pima Indian data set, verifying the effort in redesigning rules if necessary,

TABLE XI
RESULTS OF THE SEMANTIC DESCRIPTIONS FOR CASES (a) 4, (b) 19, (c) 21, (d) 5, (e) 9, (f) 7, AND (g) 1

(a)

Case 4		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		89	94	28.1	0.167	21
SDSA Semantic Descriptions	*SAS*	*The personal physical data exhibit that the person is at* **Young** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **Low**, *2-hour serum insulin is* **Low**, *body mass index is* **Medium**, *and diabetes pedigree function is* **Low**.				
	SDS	*The SDSA justifies that the possibility of suffering from diabetes for this person is* **VeryLow**. *(Possibility:* ***0.001****)*				
Medical Staff Justification		Medical staff justifies that the person is Non-Diabetes.				

(b)

Case 19		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		103	83	43.3	0.183	33
SDSA Semantic Descriptions	*SAS*	*The personal physical data exhibit that the person is at* **Young** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **Low**, *2-hour serum insulin is* **Low**, *body mass index is* **High**, *and diabetes pedigree function is* **Low**.				
	SDS	*The SDSA justifies that the possibility of suffering from diabetes for this person is* **Low**. *(Possibility:* ***0.189****)*				
Medical Staff Justification		Medical staff justifies that the person is Non-Diabetes.				

(c)

Case 21		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		126	235	39.3	0.704	27
SDSA Semantic Descriptions	*SAS*	*The personal physical data exhibit that the person is at* **Young** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **Medium**, *2-hour serum insulin is* **High**, *body mass index is* **High**, *and diabetes pedigree function is* **Medium**.				
	SDS	*The SDSA justifies that the possibility of suffering from diabetes for this person is* **Medium**. *(Possibility:* ***0.583****)*				
Medical Staff Justification		Medical staff justifies that the person is Non-Diabetes.				

(d)

Case 5		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		137	168	43.1	2.288	33
SDSA Semantic Descriptions	*SAS*	*The personal physical data exhibit that the person is at* **Young** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **High**, *2-hour serum insulin is* **Medium**, *body mass index is* **High**, *and diabetes pedigree function is* **High**.				
	SDS	*The SDSA justifies that the possibility of suffering from diabetes for this person is* **High**. *(Possibility:* ***0.826****)*				
Medical Staff Justification		Medical staff justifies that the person is Diabetes.				

(e)

Case 9		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		197	543	30.5	0.158	53
SDSA Semantic Descriptions	*SAS*	*The personal physical data exhibit that the person is at* **Old** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **High**, *2-hour serum insulin is* **High**, *body mass index is* **Medium**, *and diabetes pedigree function is* **Low**.				
	SDS	*The SDSA justifies that the possibility of suffering from diabetes for this person is* **VeryHigh**. *(Possibility:* ***0.922****)*				
Medical Staff Justification		Medical staff justifies that the person is Diabetes.				

(f)

Case 7		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		78	88	31	0.248	26
SDSA Semantic Descriptions	*SAS*	*The personal physical data exhibit that the person is at* **Young** *age, meanwhile the plasma glucose concentration in 2-hour OGTT is* **Low**, *2-hour serum insulin is* **Low**, *body mass index is* **Medium**, *and diabetes pedigree function is* **Low**.				
	SDS	*The SDSA justifies that the possibility of suffering from diabetes for this person is* **VeryLow**. *(Possibility:* ***0.016****)*				
Medical Staff Justification		Medical staff justifies that the person is Diabetes.				

(g)

Case 1		Glucose (mg/dl)	INS (mu U/ml)	BMI (kg/m^{2})	DPF	Age
Personal Physical Data		148	0	33.6	0.627	50
SDSA Semantic Descriptions	*SAS*	*The SDSA justifies that the personal physical data may be wrong.*				
	SDS	*The SDSA justifies that the personal physical data may be wrong.*				
Medical Staff Justification		Medical staff justifies that the person is Diabetes.				

TABLE XII
DIFFERENT OUTCOMES OF A TWO-CLASS PREDICTION

Actual class	Predicted class	
	Yes	No
Yes	True positive (*TP*)	False Negative (*FN*)
No	False positive (*FP*)	True Negative (*TN*)

and evaluating the overall effort in developing this fuzzy model.

- An ontology models a domain rather than represents the domain itself. This paper has presented a novel fuzzy ontology to model the diabetes domain, in which the fuzzy ontology is stored in a knowledge repository for

TABLE XIII
VALUES OF ACCURACY, PRECISION, RECALL, AND TRUE NEGATIVE RATE FOR DIFFERENT FGD RELATIONS

FGD Relation/ Semantic Description	Threshold Value	Accuracy (%)	Precision (%)	Recall (%)	True Negative Rate (%)
$FGD_{\Re_{\geq FGD_{Age\_0}}}$ / *Very Very Young*	0.7	78.3	72.3	56.2	89.3
	0.75	77.3	75.3	46.9	92.4
	0.8	76.3	76.8	40.8	93.9
	0.85	73.5	75	30	95
$FGD_{\Re_{\geq FGD_{Age\_25}}}$ / *Very Young*	0.7	82	70.5	63.8	89.3
	0.75	81.7	74.4	55.2	92.4
	0.8	80.7	75.8	47.6	93.9
	0.85	77.7	73.5	34.3	95
$FGD_{\Re_{\geq FGD_{Age\_30}}}$ / *More or Less Young*	0.7	85.6	67.4	73.4	89.3
	0.75	85.9	71.8	64.6	92.4
	0.8	85.3	73.8	57	93.9
	0.85	82.7	71.7	41.8	95
$FGD_{\Re_{\geq FGD_{Age\_35}}}$ / *Slightly Young*	0.7	89	64.1	87.7	89.3
	0.75	90.3	69.7	80.7	92.4
	0.8	89.7	71.4	70.2	93.9
	0.85	87.1	69	50.9	95
$FGD_{\Re_{\geq FGD_{Age\_40}}}$ / *Slightly Old*	0.7	89.2	58.2	88.6	89.3
	0.75	91.2	64.9	84.1	92.4
	0.8	91.2	67.3	75	93.9
	0.85	89.9	66.7	59.1	95

TABLE XIV
ACCURACY VALUES OF THE PROPOSED METHOD AND REPORT-METHODS EARLIER

Method	Accuracy (%)	Author	Method	Accuracy (%)	Author
Our study for *Slight Old*	**91.2**	**Lee and Wang**	RBF	75.7	Statlog
Our study for *Slightly Young*	**90.3**	**Lee and Wang**	NB	75.5-73.8	Ster, Dobnikar, and Statlog
PCA-ANFIS [4]	89.47	Polat and Gunes	MML	75.5 ± 6.3	Zarndt
Our study for *More or Less Young*	**85.9**		kNN, k = 22, Manh	75.5	Karol Grudzinski
ANN-FNN [8]	84.24	Kahramanli and Allahverdi	SNB	75.4	Ster and Dobnikar
GDA-LS-SVM [5]	82.05	Polat, Gunes, and Arslan	BP	75.2	Statlog
Our study for *Very Young*	**81.7**	**Lee and Wang**	CART DT	74.7 ± 5.4	Zarndt
HNFB^{-1} [7]	78.26	Goncalves et al.	DB-CART	74.4	Shang and Breiman
Logdisc	77.7	Statlog	ASR	74.3	Ster and Dobnikar
IncNet	77.6	Norbert Jankowski	CART	72.8	Ster and Dobnikar
DIPOL92	77.6	Statlog	Kohonen	72.7	Statlog
Linear Discr. Anal.	77.5-77.2	Statlog, Ster, and Dobnikar	Bayes	72.7 ± 6.9	Zarndt
Our study for *Very Very Young*	**77.3**	**Lee and Wang**	C4.5($5 \times$ CV)	72.0	Bennet and Blue
VISIT [6]	77	Chang and Lilly	kNN	71.9	Ster and Dobnikar
SMART	76.8	Statlog	IB3	71.7 ± 5.0	Zarndt
GTO DT ($5 \times$ CV)	76.8	Bennet and Blue	IBI	70.4 ± 6.2	Zarndt
ASI	76.6	Ster and Dobnikar	kNN	67.6	Statlog
Fisher discr. analysis	76.5	Ster and Dobnikar	C4.5 rules	67.0 ± 2.9	Zarndt
MLP + BP	76.4	Ster and Dobnikar	OCN2	65.1 ± 1.1	Zarndt
LVQ (20)	75.8	Ster and Dobnikar	Default	65.1	
LFC	75.8	Ster and Dobnikar	QDA	59.5	Ster and Dobnikar

a fuzzy expert system. Future works should undertake additional experiments and proofs to further improve the fuzzy ontology for the diabetes domain and to make the disease prediction much mature.

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