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OntoDiabetic: An Ontology-Based Clinical Decision Support System for Diabetic Patients

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Abstract Clinical decision support systems (CDSS) assist medical practitioners in their daily work, thereby enhancing the quality of care given to a patient. It supports them in the decision-making process and suggests appropriate treatments. The use of the ontology to build knowledge-driven decision support systems is widely adopted. Ontology is best suited to encapsulate the concepts and relationships of terms associated with the medical domain. It is suitable for capturing medical knowledge in a formal way, allowing sharing and reusing it whenever necessary. All concepts and relationships detailed in clinical guidelines can be implemented using Web Ontology Language (OWL). The reasoning mechanism is vital in any knowledge-based system. Ontology can be reasoned to recommend the suitable treatment for a patient by considering the current medical status of the patient. OntoDiabetic, an ontology-based decision support system is developed to assess the risk factors and provide appropriate treatment suggestions for diabetic patients. This paper focuses on the modeling and implementation of clinical guidelines using OWL2 rules and the reasoning process of the OntoDiabetic system. The case study is conducted for patients having the risk of overt cardiovascular disease, diabetic nephropathy and hypertension in primary health centers of Oman.

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1 Introduction

The most significant and critical part of any healthcare system is a clinical diagnosis. It is the process of identifying the nature and cause of a disease through carefully studying patient's symptoms and signs, evaluation of patient history, clinical and laboratory examinations [1]. CDSS is designed to assist the physician–patient encounter at multiple points from initial consultation to diagnosis to follow-up [48]. These systems collect, process, examine, distribute, display and store patient data. The two main categories of clinical decision support systems are knowledge-based systems and non-knowledge-based systems [2]. The general model of knowledge-based CDSS comprises of four modules: an input, output, a knowledge base and inference (reasoning engine) [3]. The system accepts the patient symptoms as input. In most of the CDSS, the complete history of the patient is provided as input. Clinical diagnosis is performed using the knowledge base and inference engine that are the most vital modules of knowledge-based CDSS. Knowledge base contains medical knowledge. It is a repository of symptoms and diseases which contains rules, mostly in the form of *If-Then* statements. For example, a typical rule might be "If the symptoms are Back Pain AND Chest Pain AND High BP, then it may result in Heart Attack." The inference engine has reasoning abilities. It examines the patient symptoms against the rules in the knowledge base, and after analyzing the symptoms, it arrives at the conclusion and generates a diagnosis report. The extracted knowledge helps the doctors to have efficient disease diagnosis and to predict the risks of several diseases, thus preventing any human error that occurs during manual diagnosis [4]. In manual diagnosis, sometimes doctors are not able to gather the complete patient medical history that may affect the diagnostic accuracy. In such cases, a clinical decision support system can guide a doctor to have better decisions. Also, the suggestions provided by the system must be carefully analyzed by the doctor before reaching the conclusion. A diagnosis made with the support of an efficient clinical decision support system substantially improves the diagnostic accuracy.

As years passed, new techniques for organizing, sharing, managing and extracting medical data were developed. The use of the ontology to model knowledge is applied in many domains, particularly in the field of medical science. Ontology is a concept used in philosophy. It gained a big attention in the area of computer science as it provides an explicit specification of conceptualizations and relationships between concepts in distinct domains [5]. It has been widely used in knowledge-driven decision support systems to assist in clinical diagnosis [6] as knowledge representation is the core of a decision support system [7]. The main advantage of ontology is the knowledge sharing, easy maintenance and reuse in similar domains [6,8]. The Semantic Web layer cake is built mainly on different levels, such as Resource Description Framework (RDF), Resource Description Framework Schema (RDFS) and Web Ontology Language (OWL), which expands expressivity at each level. Users can implement any representation based on the amount of semantics they need for their application. User-defined rules add an extra layer of expressivity to the Semantic Web. OWL was developed as an ontology language for constructing ontologies that provide high-level descriptions of Web content [9]. These ontologies are created by building hierarchies of classes describing concepts in a domain and relating the classes to each other using properties [9]. It is now widely recognized that constructing a domain model or ontology is a significant step in the development of a knowledge-based system [10]. The role of ontology is to capture knowledge and provide a commonly agreed-upon understanding of the domain [10]. With the help of ontology, the knowledge is not only human readable but also machine readable [10].

World Health Organization has recognized diabetes as a chronic, debilitating and costly disease associated with significant complications that pose severe risks for families, countries and the entire world [11]. Globally, as of 2013, an estimated 382 million people have diabetes worldwide, with type 2 diabetes making up about 90 % of the cases [12] [13]. This percentage is equal to 3.3 % of the population, with similar rates in both women and men [14]. In 2011, diabetes resulted in 1.4 million deaths worldwide, making it the eighth leading cause of death [15]. Developing countries, where resources are scarce, are expected to witness a 170 % increase in the number of people with diabetes compared to 41 % in developed countries [16]. The number of people with diabetes is expected to rise to 592 million by 2035 [13]. The high diabetes prevalence rate and the absence of an efficient knowledge-based system for predicting the risk factors for diabetic patients motivated us to develop the ontology- based clinical decision support framework [17]. This paper focuses on the modeling and implementation of clinical guidelines and the reasoning process of our CDSS. A case study is conducted for patients having the risk of overt cardiovascular disease, diabetic nephropathy and hypertension in primary health centers of Oman.

The organization of the remainder of the paper is as follows: Sect. 2 describes the literature review and diagnostic inaccuracy in knowledge-based CDSS. Section 3 explains the methodology. This section outlines the system architecture, the ontology design and the reasoning. Section 4 illustrates the implementation of clinical guidelines. It describes OWL2 rules and the rules used in the OntoDiabetic system. In Sect. 5, graphical user interfaces are explained. Section 6 presents the ontology testing and results. Section 7 discusses the output accuracy and the analysis of the performance metrics of the system. Section 8 displays a sample output followed by evaluation of the system in Sect. 9. Section 10 provides the conclusion and future.

2 Background

The integration of clinical decision support (CDS) into the computer-based patient record (CPR) reduces medical errors, enhances patient safety, decreases unwanted practice variation and improves patient outcomes [41]. This section explains the related work and the diagnostic inaccuracy in knowledge-based CDSS.

2.1 Previous Work

A group of researchers from Taiwan proposed a data mining technique to determine the time dependency pattern of clinical pathways for curing brain stroke [42]. The time dependency patterns predict the paths for new patients. Also, the resulting clinical pathways facilitate the continuous improvement of assigning more suitable paths to patients. Thus, the healthcare procedure is made more effective and efficient. The evidence-based medicine (EBM) integrates clinical experience and patient values with the best available research information [45]. It is best described as “the explicit, judicious and conscientious consideration of current best evidence from research for making judgments about the care of individual patients” [46]. Accessing and applying valid and relevant summaries of research evidence provides more realistic and efficient use of EBM. A decision support system for evidence-based medicine (EBM) links the data warehouse and data mining techniques [43]. Here, typical patterns of knowledge useful in the diagnosis process such as patients medical history, diagnosis, or therapy are analyzed using data warehousing techniques, such as OLAP queries. Text mining techniques are also proposed to mine the abundant textual information within the clinical records of many hospitals.

Clinical pathways are multifaceted plans of the best clinical practice in specified groups of patients with a particular diagnosis that aid the coordination and delivery of high-quality care [44]. It standardizes the medical care and increases the patient satisfaction. An integrated clinical evidence (ICE) system that consists of knowledge management, data mining, case-based reasoning (CBR) and Web-based systems is presented by researchers from Malaysia [46]. CBR systems retrieve a similar set of cases from the past clinical cases and synthesize the retrieved solutions to arrive at a conclusion for the given clinical case. knowledge discovery in databases (KDD) is also used in the implementation of CDSS. Researchers from Portugal proposed a KDD-based architecture for CDSS for intensive care medicine [47]. The knowledge base is constructed using KDD methodology. Data repository is filled with data from available data sources that can be used for automatic updates to the knowledge base.

Knowledge-based CDSS has been broadly reported in the literature. MYCIN embeds decision rules into an expert system that provides interactive consultation [18]. MYCIN uses a knowledge base of approximately 600 rules and a simple inference engine. The University of Utah, School of Medicines, developed Iliad, a medical expert system software using Bayesian network as classifier [19]. Kahn et al. suggested a mammography system Mammonet based on Bayesian networks as a useful tool for mammographic decision support [20]. A rule-based program, IMM/Serve, is being developed to help childhood immunization for initial use [21]. A Semantic Web approach to model, the clinical practice guidelines in a Breast Cancer Follow-up Decision Support System, is presented by Abidi et al. [22]. Ceccarelli et al. developed a knowledge-based CDSS for oncology, where both ontology and a rule set were proposed [23]. Mouley Bouamrane presented OWL DL ontology for a preoperative risk assessment, recommended tests and clinical precaution protocols [24]. O'Connor et.al estimated the impact of an electronic health record-based diabetes clinical decision support system on control of hemoglobin A1c (glycated hemoglobin), blood pressure and low-density lipoprotein (LDL) cholesterol levels in adults with diabetes [25]. A group of researchers from Spain presented a knowledge engineering diagnosis support tool for the detection of Alzheimer disease where ontologies and semantic reasoning play a fundamental role [26]. Mahmud, F.B. attempted to map CDDS functions with clinical domain and proposed an ontologically based CDSS for weaning ventilation [27]. Farmer et.al have developed a prototype knowledge-based diagnostic CDSS based on Bayesian reasoning to diagnose six common musculoskeletal shoulder pathologies [28]. The system was tested by comparing its diagnostic outcome against 50 case studies with a known diagnosis by radiological imaging [28]. Wang et al. proposed a design of the system framework that accepts the symptoms of a patient as input, and conduct a pre-diagnosis by using disease symptom ontology [29]. In 2014, an attempt was made by Piyush and others to design and develop such diagnosis system, using fuzzy logic rule base [30]. Tian proposed ontology-based decision support system for interventions based on monitoring medical conditions on patients in hospital wards [31]. We have reviewed many well-known CDSS. Of all these, relatively little work is done in the development of decision support systems for risk assessment prediction of diabetic patients.

2.2 Diagnostic Inaccuracy in Knowledge-Based CDSS

The intelligence of any clinical decision support system depends on its knowledge base and reasoning algorithm [10]. In the medical domain, some CDSS fails in providing completely accurate advice to the physician. This problem of diagnostic inaccuracy is mainly due to the following reasons [32]:

Inappropriate design of knowledge base of CDSS Different representation patterns such as logic, procedural, graph/network and structured are used to represent the domain knowledge. Each of these schemes may have advantages and disadvantages, and these may affect the process of diagnosis.

Limitation of tools/technologies used in the implementation of CDSS The rules in the knowledge base is coded using programming languages or related technologies. The retrieval of the diagnostic report depends on the clarity of representation of knowledge. So the limitations of the programming language may affect the precision of diagnosis.

Issues related to the reasoning engine The diagnostic accuracy also depends on the type of reasoning strategies used in the system.

Issues related to inferring new knowledge Knowledge base systems update their knowledge by adding inferred knowledge to the knowledge base. Artificial neural networks, Bayesian networks, genetic algorithms, etc. are the techniques used. So the inferring of knowledge depends on the excellence of methods used.

3 Methodology

3.1 OntoDiabetic System Architecture

OntoDiabetic is an ontology-based clinical decision support system for risk analysis and prediction of diabetes mellitus. Figure 1 shows the architecture. OWL is used to represent

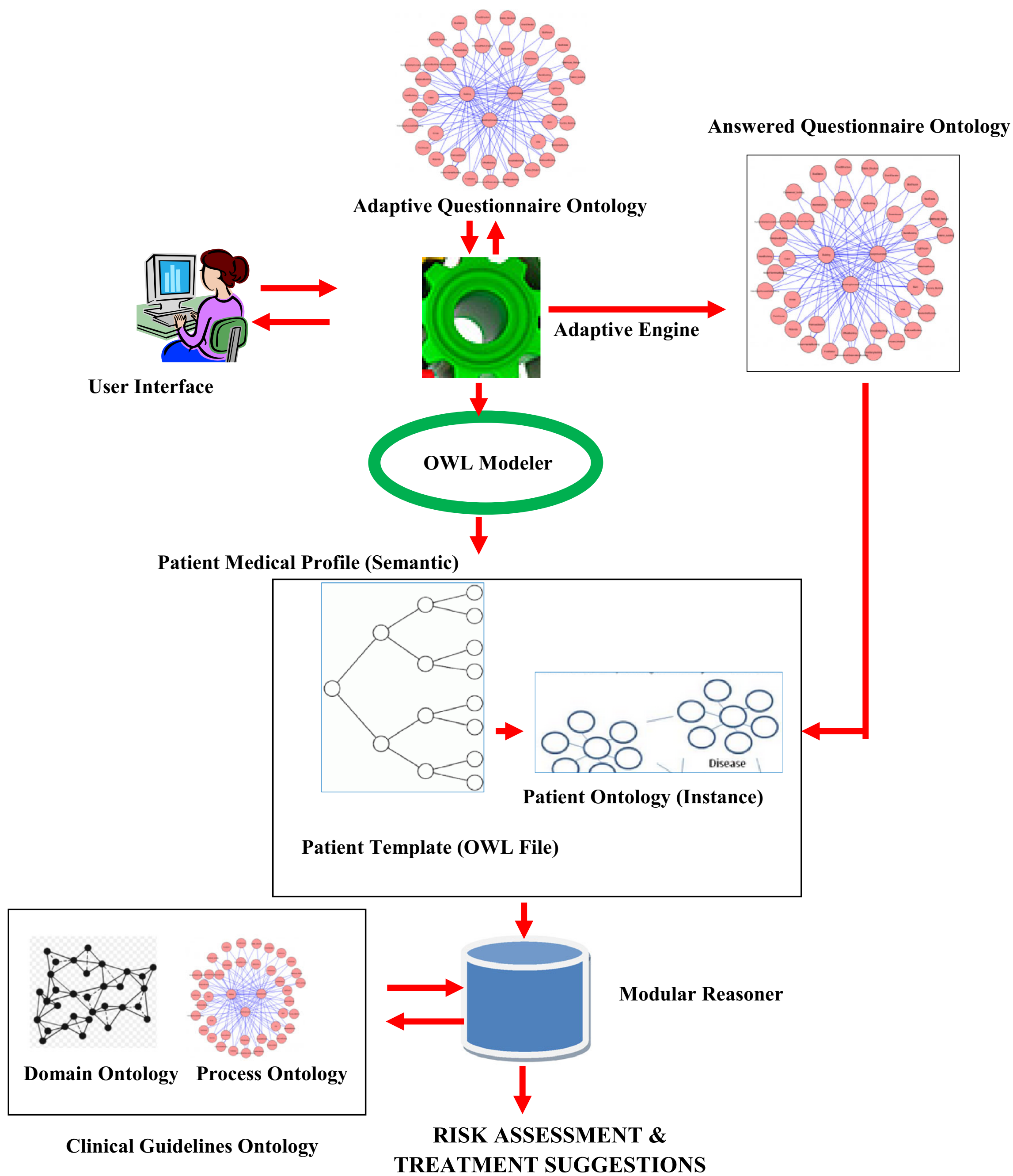


Fig. 1 OntoDiabetic architecture

the domain knowledge. Besides, rules are used to extend the expressivity of OWL. The system functions are follows: Before going to the clinic, the patient registers in the corresponding Web application by answering a questionnaire. Once the patient registration procedure is completed, the patient is served with a questionnaire, which is generated by the AdaptiveQuestionnaire module. The AdaptiveQuestionnaire module dynamically generates the set of questions from Questionnaire ontology. The questions are made according to the patient context. For example, if a patient is not a smoker, then the concerned patient is not required to answer further questions related to smoking. The questionnaire collects information from the patient regarding the personal details, diabetic history, family history, physical activity history, complications history, medical history, etc. This process is analogous to a doctor interviewing the patient to know the patient history before diagnosis and treatment. The system stores the patient history in AnsweredQuestionnaire ontology. Later, when a patient visits the hospital, a nurse, lab technician, dietician and doctor also provide additional inputs to the patient's profile. The dietician adds nutritional history, and the lab technician adds appropriate laboratory test values. The nurse adds information like vital signs by observing the patient. A patient semantic profile is then automatically generated. Now clinical guidelines (OWL2 rules) are applied to the patient profile, from which the scores of risk factors and appropriate treatment suggestions are produced.

3.2 Ontology Design

The system consists of two main ontologies, viz. the **diabetic patient clinical analysis ontology** and the **semantic profile**.

3.2.1 Diabetic Patient Clinical Analysis Ontology

This ontology is the core of the system. It encapsulates all the information required to analyze the patient information, examines the risks, computes risk score and suggests treatment procedures, according to the given clinical guidelines. It consists of five sub-ontologies. *AdaptiveQuestionnaire* ontology, *AnsweredQuestionnaire* ontology, *Patient* ontology, *Domain* ontology and *Process* ontology (clinical guidelines).

3.2.2 AdaptiveQuestionnaire Ontology

This ontology consists of Question types as classes and actual questions as its instances. The parent classes in *AdaptiveQuestionnaire* ontology represent the main classes in the domain. They are *Question_Bank*, *Question*, etc. *Question-Bank* is an abstract class. It consists of different subclasses according to the category. These subclasses contain instances that correspond to that particular category. For example, the instances of *DieticianQuestionBank* class are questions coming under nutritional history. The subclasses of *Question* class are used to hold each type of question. For example, instances of *MultipleChoiceQuestion* class are multiple choice type questions. The object property '*contains'* is used to associate the class *Question_Bank* with the class *Question*. Data properties *question no* and *question-part* are used to keep the question number and the question text. The object properties *hasChoice* and *subQuestion* maintain a set of choices and one or more sub-questions if any. The *Questionnaire* class is instantiated (individual created) for each run of the questionnaire, i.e., for each patient registration. Additionally, it contains a class called *Sequencer* which associates rules to each sequence member to store the sequence or order of questions in the questionnaire. This ontology schema is instantiated with its corresponding values when a new patient registration process starts. Figure 2 shows a screenshot of *Question* class and its subclasses in *AdaptiveQuestionnaire* ontology in ProtegeVOWL [33]. The Visual Notation for OWL Ontologies (VOWL) provides a visual language for the representation of ontologies [33].

3.2.3 AnsweredQuestionnaire Ontology

AnsweredQuestionnaire ontology contains information entered by the patients and is used as a base to create Semantic Patient profile. The instances store the answers entered by each patient.

3.2.4 Patient Ontology

Patient ontology consists of all patient records stored in the form of ontology. Each patient is an individual (instance) of this ontology and is automatically generated from *AnsweredQuestionnaire* ontology using Property Insertion and Individual Insertion mechanisms. PatientTemplate.owl contains the schema for *Patient* ontology. In other words, PatientTemplate is the schema for a patient's semantic profile. The patient semantic profile is created by inserting the necessary information extracted from *AnsweredQuestionnaire* ontology.

3.2.5 Domain Ontology

Domain ontology defines all the terminologies in the clinical guidelines. The purpose of this ontology is to define the axioms used in the rules for *Process* Ontology. Figure 3 shows a screenshot of *Domain* ontology in ProtegeVOWL [33].

3.2.6 Process Ontology (Clinical Guidelines)

Process ontology encapsulates the diabetics guidelines. The NICE (National Institute for Health and Care Excellence) guidelines are used as a reference for ontology creation [34]. It models the guidelines (flowchart) as ontology. We have used two different approaches for ontological modeling of the guidelines. In the first method (Fig. 4), each concept/class is made as analogous to a state of finite state machines or process. Except for connector symbol, each symbol in the flowchart is modeled as a state/sub-process.

When the processing reaches a particular state, it is assumed that it has completed the processing up to the previous state. In other words, the precondition to reach a particular state is that the previous processes in the chain are complete. For example, in a particular instance of time if the current state of process is D, then it means that it has completed the sub-processes A and B. In other words, reaching

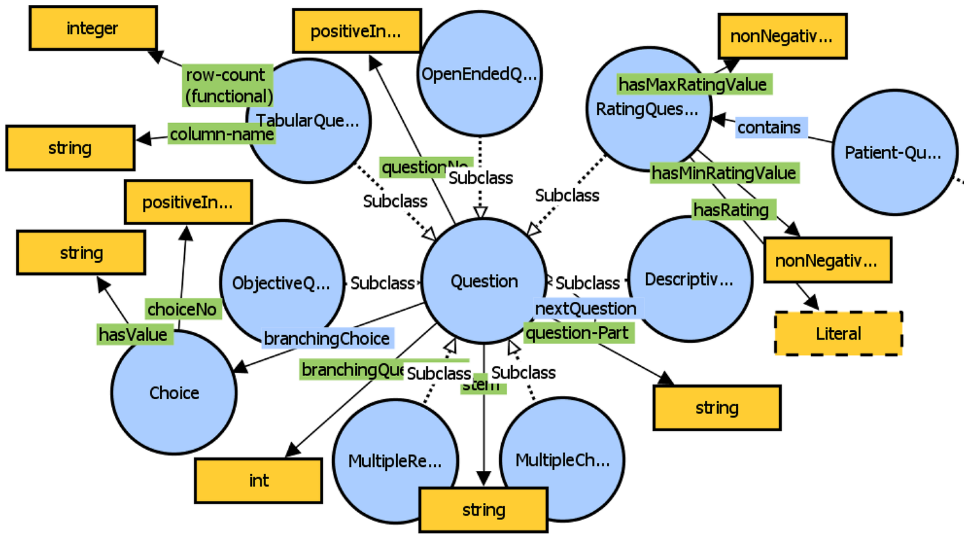


Fig. 2 AdaptiveQuestionnaire ontology

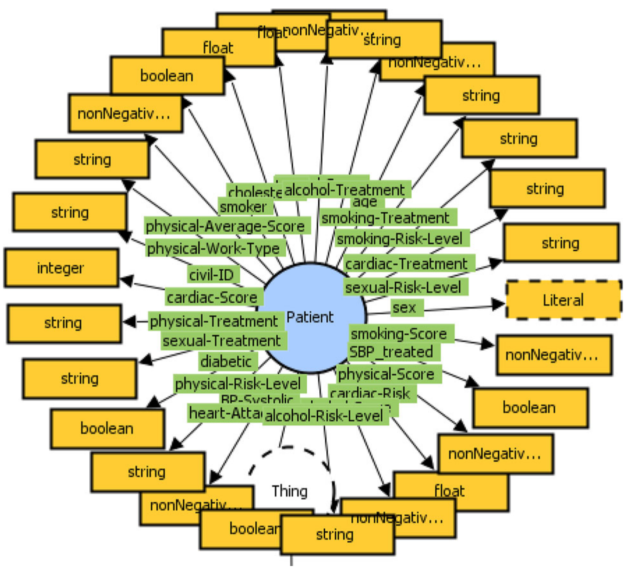


Fig. 3 Domain ontology

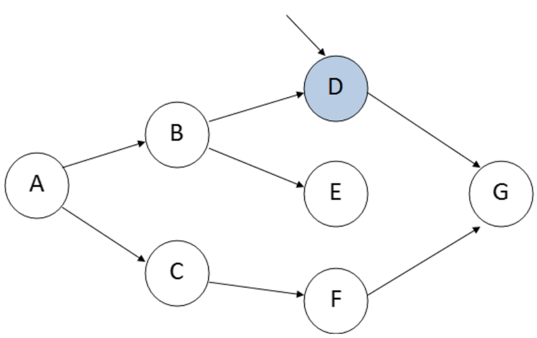


Fig. 4 Ontological modeling of guidelines—approach 1

state D means that it has passed through states A & B. The state is changed in such a way that the next state depends only on the current state and the conditions.

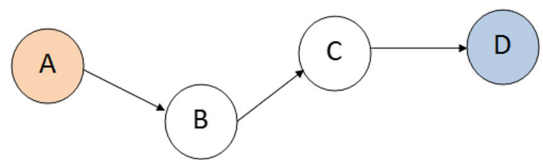


Fig. 5 Ontological modeling of guidelines—approach 2

The second approach used in this model is to design guideline rules from every path that originates in the start symbol of the flowchart and ends with a leaf node (Fig. 5). For example, the rule begins with node A and ends in a leaf node D satisfying the conditions B and C.

The modeling of clinical guidelines of OntoDiabetic CDSS uses both the approaches. Also, each execution path is computed from the clinical guidelines flowchart and is converted to rules, in one step or more.

3.2.7 Semantic Profile

Semantic profile is an OWL file that encapsulates patient details as entered by the patient, nurse and doctor. This file is initially generated as soon as the patient submits the questionnaire. Later, the same is updated by the clinic officials (e.g., nurse) and finally by one or more doctors. The structure (schema) of the semantic profile follows from *AnsweredQuestionnaire* ontology and *Patient* ontology. So, even though it is an independent OWL file, it can be considered as an instance of *AnsweredQuestionnaire* ontology and *Patient* ontology. The former is initially created by the application, and the latter is automatically generated from the former by using the OWL2 feature called Property Insertion.

3.3 Ontology Reasoning

Reasoners are application software for computing or deriving new facts from existing knowledge bases. A rule-based inference engine applies rules with data to reason and derive new facts. When the data match the rules conditions, the inference engine can modify the knowledge base, e.g., fact assertion or retraction, or to execute functions, e.g., display the derived facts. There are two main strategies of reasoning, forward chaining and backward chaining [35]. Forward chaining starts from existing facts and applying rules to derive all possible facts, while backward chaining starts with the desired conclusion and performs backward chaining to find supporting facts. User applications interact with inference engines via APIs (application programming interfaces). These APIs typically support selecting reasoning strategies, features, operations, storing facts, querying the result data from the knowledge base, etc.

We have adopted the forward chaining strategy in OntoDiabetic reasoning (Fig. 6). Rules are applied to the asserted facts, and the entailed statements are immediately added to the knowledge base until it reaches the conclusion (inferred fact). If the number of rules is more, this method may be inefficient. For example, if we have r rules with an average of p premises and f facts, then $r \times f^p$ comparisons are needed on each cycle to find rules to be fired. For a knowledge base with 100 rules and an average of three premises and ten facts, 1,00,000 comparisons per cycle are required. The reasoning can be more precise and formal if we have the strict adequate specification for the underlying knowledge representation scheme, so the binding of knowledge representation system and the reasoning component is noticeable.

To improve the performance of the reasoning process, we have implemented a modular approach in the reasoning process. The complete clinical guidelines and the patient semantic profile are not reasoned together. Instead, the similar clinical guidelines (rules) are grouped together, and priority is assigned to each group. For example, to reason the patient risk due to smoking, the corresponding smoking treatment guidelines and selective rules are reasoned together with the patient profile. This approach reduces the number of comparisons needed in each cycle.

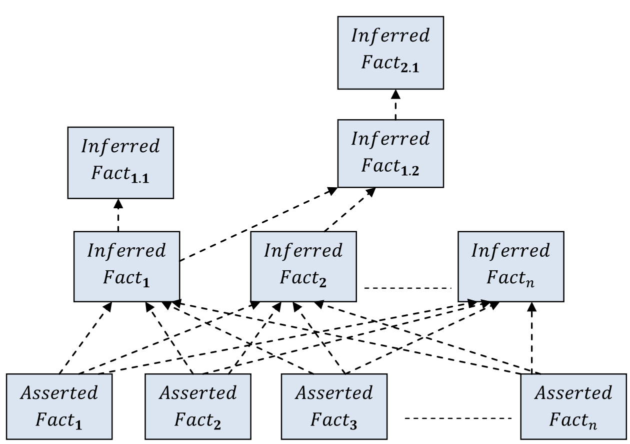


Fig. 6 Forward chaining inference

4 Implementation of Clinical Guidelines

4.1 OWL2 Rules

Since the earliest development of intelligent systems, rules were used to represent knowledge in such systems [36]. Rules give an additional level of expressivity that cannot be offered by Web Ontology Language (OWL). It enhances the ontology language by allowing one to describe relations that cannot be described using description logic used in OWL [36]. The rule language also allows sharing and reuse of existing rules between different systems. OWL ontology is extended using rules. OWL2 reasoners such as Pellet and HermiT can be used to reason over such ontologies extended using these rules.

In Semantic Web, a rule is expressed in the form of *If-then* statements containing logical functions and operations. A rule consists of an antecedent (body of the rule) and a consequent (head of the rule). The antecedent contains conditions combined using logical operators, while the consequent part contains conclusions. If the rule statement(s) is true, new knowledge is added to the knowledge base. Informally, the rule can be read as: If the body is true, then the head must be true [37]. These rules can be defined in different rule languages or formats. Variables are prefixed with a question mark; atoms in the rule body and rule head are separated by commas, and a dash followed by a 'greater than' symbol is used to separate the rule [37].

hasSibling(?x, ?y), Man(?y) - > hasBrother(?x, ?y) [36]

To date, a wide variety of rule languages have been used in Semantic Web, but there is no standard language yet. Semantic Web Rule Language (SWRL) is the most commonly used language to express rules [38]. But the biggest drawback of Semantic Web Rule Language (SWRL) is that it can quickly make ontology undecidable. The development of DL-safe rules solves the problem. DL-safe rules bind known instances to the ontology. So if there are no instances that match the query, then DL-safe rules will not execute the consequent even if the rule is a valid one. The rules used here is the Manchester version of OWL2 rules [38]. These rules can be directly integrated into OWL2 ontologies.

4.2 OntoDiabetic Rule Expressions

Domain ontology defines the concepts/ axioms used in the rules. Inference rules are written in terms of domain concepts. Figure 7a, b shows the guidelines flowchart related to treatment suggestions of patients with a history of the overt cardiovascular disease.

Clinical guidelines are converted into rules. Rules are defined for every path that originates in the start symbol of the flowchart and ends with a leaf node. The reasoner, by default, takes only predefined relationships for inference (e.g., *subClassOf*, *instanceOf*). Otherwise, rules have to be explicitly defined for the same. This property is made use to move the process from one state to another. Each state is associated with the rule (precondition & transition rule) which makes the reasoner advance the process from one stage to another. For example, the modeling of the highlighted part in the flowchart is shown in Fig. 8.

In Fig. 8, each state is represented in the oval symbol. Depending upon the conditions, the next state is achieved. The conditions and rules are given below:

Rule 1

Person(?p) ˆ CardiacHistory(?p, false) ˆ Age(?p,?aVal) ˆ lessThan
(?aVal,40) ˆ LDL (?p,?LDLvalue) ˆ greaterThan (?LDLvalue,2.6) → High_LDL(?p)

Here the reasoner employs forward chaining inference. For an instance ‘p’ of class Person, the input values of CardiacHistory, age, and the LDL are checked. If the CardiacHistory is false, if the age is less than 40, and if the LDL value is greater than 2.6, it is concluded that the patient has High LDL. This knowledge (entailed statement) is added to the knowledge base. In other words, a new state is reached.

Rule 2

High_LDL(p) ˆ PatientOnStatin(?p,false) ˆ eGFR(?p, ?eGFRvalue) ˆ greaterThan(?eGFRvalue,30) → Normal _eGFR(?p)

In Rule 2, new facts are derived. For example, the inferred fact from Rule 1 is checked here with other knowledge. Rule 2 tests whether the patient is currently taking the medicine ‘Statin’ and also the value of GFR. If the patient is presently

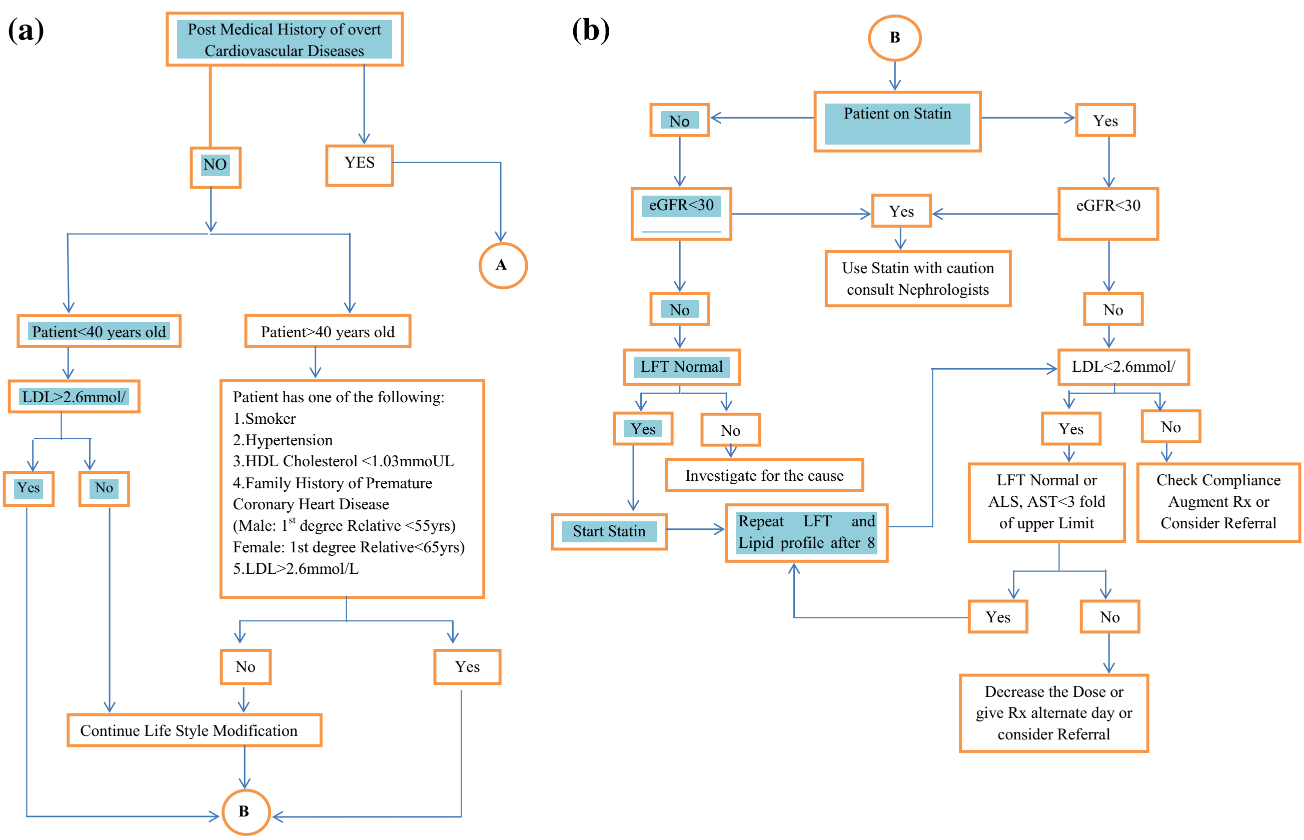


Fig. 7 **a** Clinical guidelines for patients with history of overt cardiovascular disease. **b** Clinical guidelines for patients with history of overt cardiovascular disease

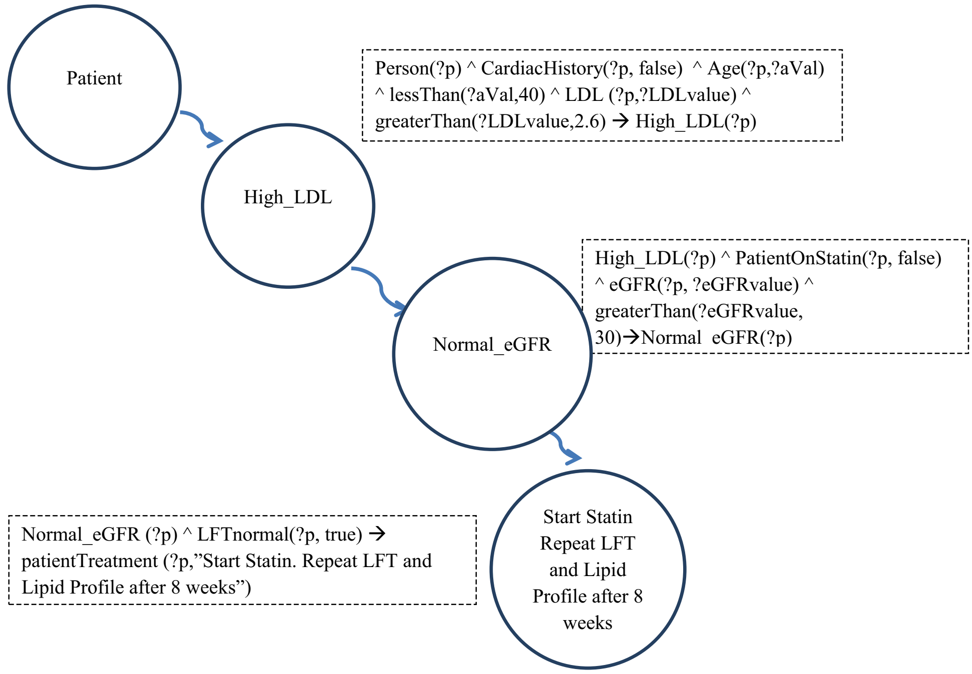


Fig. 8 Modeling of highlighted guideline in Fig 7a, b

using the medication 'Statin' and if the eGFR value is greater than 30, it is concluded that the patient has a normal eGFR. The information Normal_eGFR(?p) is added to the knowledge base.

Rule 3

Normal_eGFR(?p) ˆ LFTnormal(?p, true) → patientTreatment (?p,"Start Statin. Repeat LFT and Lipid Profile after 8 weeks")

Rule 3 checks the inferred fact in Rule 2 along with other patient information. It checks whether the patient has a normal LFT. If LFT value is within the limit and if the patient has a Normal eGFR, then the treatment "Start Statin. Repeat LFT and Lipid Profile after eight weeks" is suggested.

Person (?p) is a fact. Rule 1 is an implication with Person (?p) as a premise. If all the other premises are true, the consequent High_LDL(?p) is added to the knowledge base. Now the fact High_LDL(?p) and the other premises which are *true* leads to the addition of the consequent Normal_eGFR(?p) to the knowledge base. Finally, the fact Normal_eGFR(?p) with the other *true* premise results in the addition of the final inference patientTreatment. Rules are applied to the asserted facts, and the entailed statements are immediately added to the knowledge base until it reaches the conclusion (inferred fact).

For example, if a diabetic patient has high cholesterol, usually doctors prescribe the medicine '*Statin*' to lower the cholesterol. Our system initially checks the cardiac history of the patient before suggesting the medicine. Similarly, a bunch of rules is verified by the system before recommending '*Statin*' as the medicine.

5 Graphical User Interfaces

Patients will be provided with a graphical user interface to fill the personal details and medical history. Nurse, dietician, doctor, etc. are provided with different user interfaces. All user interfaces are secured using a username and a password.

5.1 Patient Interface

A patient is presented with a questionnaire where he/she can enter his/her personal information, diabetic history, family history, smoking history, alcohol history, physical activity history, etc. (Fig. 9). The *AdaptiveQuestionnaire* ontology generates questions in the dynamic questionnaire automatically. Here the main benefit is that the patient can enter all these information at their convenience from anywhere. Initially, the answers are stored as a single instance of *AdaptiveQuestionnaire* ontology. When a patient completes entering all the above details, a patient profile is automatically created which is called the semantic profile. The patient semantic profile is created as an individual instance of *Patient* ontology.

5.2 Clinician Interface

At the time of appointment in the health center, clinicians (nurse, dietician, etc.) interview the patient and collect other relevant information. Nurse interface allows a nurse to enter the vital signs of the patient such as temperature and BP,

Fig. 9 Patient user interface

SMOKING HISTORY		
15	Do you smoke?	○ Yes ○ No
16	If yes, for how many years you are smoking?	
17	How many cigarettes do you smoke per day?	10 or less
18	How soon after you wake up do you smoke your first cigarette?	0-5mins
19	Do you find it difficult to refrain from smoking in places where smoking is not allowed? (E.g. hospitals, government offices, cinemas, libraries etc.)	○ Yes ○ No
20	Do you smoke more during the first hours after waking up than during the rest of the day?	○ Yes ○ No
21	Which cigarette would you be the most unwilling to give up?	○ First in the morning ○ An of the others
22	Do you smoke even when you are very ill?	○ Yes ○ No

Fig. 10 Clinician user interface

CBC INFORMATION		
1	Hemoglobin	
2	MVC	
3	MCH	
4	PLT	
5	WBC	
Urea & Electrolytes		
6	Sodium	
7	Potassium	
8	Urea	

and the dietician inputs the nutritional history of the patients (Fig. 10). The semantic profile created earlier updates these details.

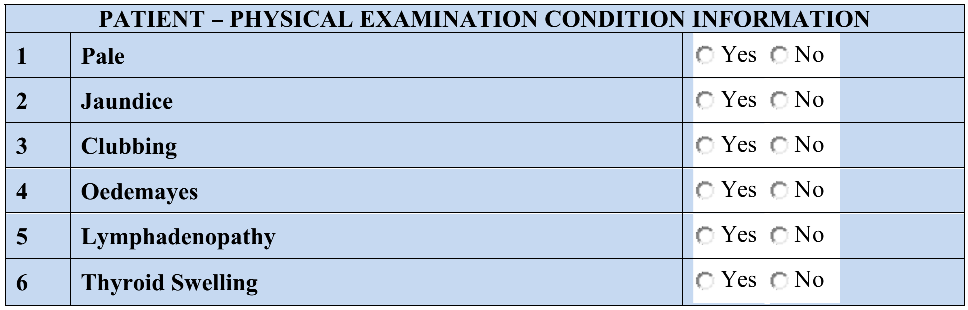
5.3 Doctor Interface

After the clinician's interview, the patient is seen by the doctor. Initially, the doctor interface displays the semantic profile of the patient. Doctors can view the complete history of the patients along with the current information entered by the nurse. The system also displays the score, risk level and treatment suggestions according to cardiovascular, sexual, physical activity, alcohol and smoking history of the patient. Doctor examines the general physical condition of the patient and updates the system (Fig. 11). As per the current status of the patient, suitable laboratory tests can also be suggested by the doctor. *Clinical guidelines* ontology consists of rules that recommend appropriate treatment as per the risks and complications of a patient.

6 Ontology Testing and Results

A real-time environment is adopted to test the performance of the proposed system. The existing Al Shifa system used in health centers of Oman is used to compare the validity of our method. Two hundred and fifty (250) diabetic patients were chosen from various health centers of Oman to conduct the analysis of OntoDiabetic CDSS. Risk assessment of the diabetic patients who have different medical histories has been done using the ontology-based CDSS and has been compared with the manual evaluation of risk assessment by the medical doctors. Out of 250 test cases, 123 were general diabetic patients having fewer complications. Predicting the risk of these 123 diabetic patients in five different parameters such as smoking, alcohol, physical, sexual and cardiac that mainly affects diabetes was conducted. On an average, the system has shown 74 % efficiency in the reasoning of risk assessment, thus producing correct risk prediction in 91 test cases on an average. Out of the remaining 26 % of the cases,

Fig. 11 Doctor user interface



PATIENT – PHYSICAL EXAMINATION CONDITION INFORMATION		
1	Pale	Yes No
2	Jaundice	Yes No
3	Clubbing	Yes No
4	Oedemayes	Yes No
5	Lymphadenopathy	Yes No
6	Thyroid Swelling	Yes No

Table 1 Test results—general diabetic patients

S. no	Risk factors	Successful test cases	Accuracy (%)
1	Smoking	96	78
2	Alcohol	88	72
3	Physical activity	102	83
4	Sexual	91	74
5	Cardiac	75	61

the system has predicted high risks (for more precautions) in 15 % (18 patient cases), which was not required according to the actual diagnosis; 11 % (14 patient cases) were predicted having less risk, which was not true in the manual diagnosis based on the laboratory results. Out of 74, 31 % cases were wrongly predicted by medical experts, due to the lack of experience and inefficiency in collecting sufficient patient history; 43 % of the cases were diagnosed alike, and similar predictions were done by the OntoDiabetic system and the doctors. Table 1 shows the results of risk prediction in general diabetic patients.

The remaining 127 patients fall in any of the three complications, overt CVD, diabetic nephropathy and hypertension. Fifty-two test cases of patients having overt cardiovascular diseases were assessed. Out of this, in 83 % cases, OntoDiabetic system diagnosed correctly and generated appropriate alerts and treatment suggestions. Thirty-four diabetic nephropathy cases were tested, and in 79 % cases, the warnings and recommendations of our system were valid. Forty-one patients having hypertension were diagnosed by the system and 85 % accurate alerts, and treatment recommendations were generated. The incorrect treatment suggestions of the unsuccessful test cases (17 %) of overt cardiovascular diseases were mainly due to the missing/ inaccurate entry of values of laboratory tests. It happened because the patients failed to produce appropriate laboratory reports. In the case of diabetic nephropathy, we used prescription data obtained from the Al Shifa system which is entered by the physician. Several laboratory tests are involved in the treatment of diabetic nephropathy patients. Out of 21 % unsuccessful cases, 13 % inaccuracy was due to wrong data entry and the remaining 8 % was due to the incorrect reasoning done by the modular reasoner. The incorrect reasoning happened due to the semantic inconsistency that occurs when a class hierarchy incorrectly classifies a concept as a subclass of another concept to which it does not belong. The failure cases (15 %) of hypertension patients were due to irregular follow-up of their treatment in the health centers, resulted in missing data and so the system were not able to generate suitable alerts. Table 2 presents the results of diagnosis of diabetic patients with complications.

7 Discussion

7.1 Output Accuracy

The patients tested were selected from different categories such as general diabetic patients, those with post-medical history of the overt cardiovascular disease, diabetic nephropathy and hypertension. Each patient's complete medical history, laboratory test values, vital sign values, currently taking medicines and the dosage, etc. was fed to the system. These test patients were inserted as individuals in the ontology. The system automatically generates a patient semantic profile that is an OWL file. Reasoner reasons the data in the patient profile with the clinical guidelines calculates the risk and suggests suitable treatments. We compared these results with the risk assessment done manually by the doctors.

The OntoDiabetic system generates two different outputs in terms of clinical terms. The primary output is the calculation of score and prediction of risk of diabetic patients in five various parameters that mainly affect diabetes. Of the five factors, the physical activity risk assessment had more successful test cases compared to the risk assessment of other factors as shown in Fig. 12. The cardiac risk assessment had more unsuccessful test cases compared to the risk assessment of other factors. Assessment of cardiovascular risk is done based on Framingham risk score algorithm [39]. In this algorithm, the risk is calculated based on seven factors such as gender, age, total cholesterol, HDL cholesterol, systolic blood pressure, hypertension history and smoking history of patients. In some of the patient cases, values of total cholesterol and HDL cholesterol were missing as the

Table 2 Test results—diabetic patients with complications

S. no	Complications	No of test cases	Successful test cases	Accuracy (%)
1	Overt cardiovascular disease	52	43	83
2	Diabetic Nephropathy	34	27	79
3	Hypertension	41	35	85
Total		127	105	

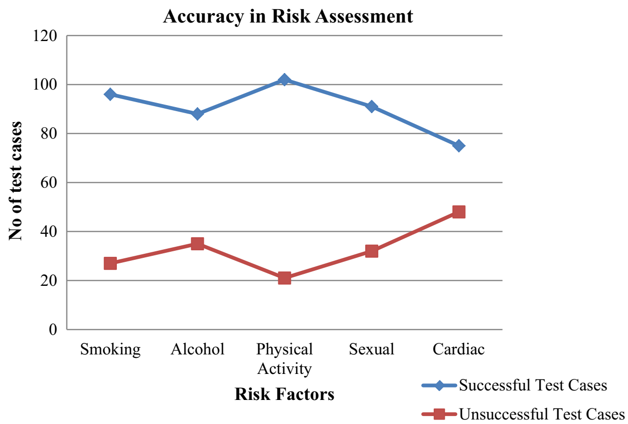


Fig. 12 Accuracy in risk assessment

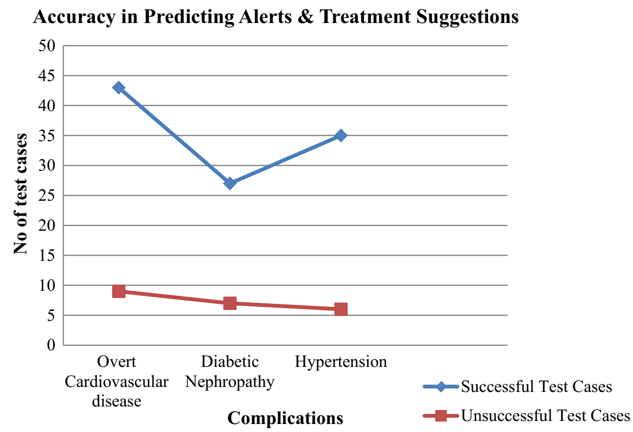


Fig. 13 Accuracy in predicting alerts and suggestions

patients didn't follow the prescription of doctors to conduct laboratory tests. It affected the calculation of the cardiac risk score. Since the ontology uses open-world assumption (OWA) [40], these missing values are considered to be unknown. So the increase in unsuccessful test case rate is mainly due to the insufficiency of data, and thus ontology reasoning failed to complete the assessment of cardiac risk scores.

The second output is providing alerts/recommendations and suggesting suitable treatments for such diabetic patients having three main complications, post-medical history of the overt cardiovascular disease (CVD), diabetic nephropathy and hypertension. Of the three difficulties, the alerts and treatment suggestions of patients having hypertension were the most accurate and diabetic nephropathy patient cases produced least accurate results (Fig. 13).

7.2 Other Performance Metrics Analysis

Ontology is a description of concepts and the relationships between concepts. Classes that are used to represent the concepts and properties are used to denote the relationships between the classes. Each patient history is stored as an instance of the corresponding class. Since the ontology has the flexibility of sharing and extending, we can update the system for more inputs and more rules in the future, which is difficult in a database system. The accuracy of the outputs identifies the efficiency of the system. But other than that, the OntoDiabetic system was also tested for the loading time, query retrieval time, query completeness and soundness. The time needed to load the ontologies in the proposed system is dependent on the number of inputs. The more the inputs, the more is the loading time. Query response time is fast when small queries are entered and for less number of inputs. We have done performance analysis based on parameters such as loading time, response time, information retrieval and query completeness.

7.2.1 Loading Time

In the OntoDiabetic system, the questionnaire is generated from *AdaptiveQuestionnaire* ontology. Then the patient semantic profile was created automatically as an individual instance of *PatientOntology* from the *AnsweredQuestionnaire* ontology. The two ontologies—*Domain* ontology and *Process* ontology—are used to represent the clinical guidelines. The load time is measured as the time for displaying the data from/to the ontology to/from the user interfaces. Also, the processing time such as parsing and reasoning of ontology is counted as loading time. We have compared the loading time of the existing database system and OntoDiabetic system and found that loading time of our system is more (about 1 minute) than that of Al Shifa system.

7.2.2 Response Time

The efficiency of the system is not just considered as the quality of search results, but also with the speed with which the

Table 3 Sample output

Treatment suggestions		
1	ACR checkup	Repeat ACR after one year
2	GFR checkup	NIL
3	Valsartan status	Upgrade dosage to 160BID after one month. Repeat RFT after a week.
4	Cardiac	Continue life style modification.
5	Hypertension treatment	Do GFR test

results are obtained. The response time is the amount of time taken for the execution and to display the output. The Onto-Diabetic system generates the patient semantic profile, the scores of risk factors, alerts and treatment suggestions. On an average, we found that the response time for displaying the scores, alerts and recommendations were more compared to the generation of the semantic profile since ontology reasoning is involved in that. When compared to Al Shifa system, we found that the time taken to display the patient profile is almost same for both systems.

7.2.3 File Size

Each patient semantic profile is created as an OWL file (<200 KB) which has very less size as compared to a database file.

8 Sample Outputs

Table 3 shows the treatment suggestions for a patient with chronic diabetes. The patient semantic profile was analyzed with the family history of cardiovascular disease and hypertension. To check the risk of developing diabetic nephropathy, and cardiovascular disease, we add the urine albumin test (ACR) value to the semantic profile. The rea-

Table 4 Sample Questions—usability test Questionnaire

Functionality
The system shows the overall completeness and appropriateness in system modules specification
The system accurately identified the risk of patients with different parameters
The system gathers the complete medical history of patients
The system ensured that the patient information is protected from unauthorized access
Usability
The users clearly understand the screen interface because it is self-explanatory and encourages obtaining help to learn how to use the software
When browsing each module of the system, the users quickly understand which and what point of the program he is using
While using the system, it is found that the various functions are well integrated
The user felt very confident in using the system
Reliability
The system requirements can change over time, efficiently and effectively by using maintenance features
The system can easily recover the bugs caused for particular input values into the system
The system can go back to the normal state and save the last saved checkpoint when the system unintentionally shut off
The system efficiently retrieves the accidentally deleted data by providing accurate backup and recovery module
Efficiency
The system is very fast to use
The system had enough storage capacity to store thousands of patient files
The system provides the fast processing of decision-making process because of enough memory
The system can run on any different Web browser
Maintainability
The system efficiently adapts if there are new modifications added in the system module
The system has the capability to store the information and is well organized
The system shall react to all user commands and data entries within 5 s
Portability
The system can handle the offline clinical decision support system if online is not working
The system can handle the installation of any new software application

Table 5 Dataset for usability test

Category	Number of users
Doctor	21
Nurse	45
Lab Technician	10
Dietician	9
Patient	60

soner compares the values with the rules related to the guideline of ACR limits and found that the value (<1) is typical, provided the suggestion of repeating the test after one year. LDL level was found to be less than 2.6 mmol/L, an ideal range for people at risk of CVD. So the suggestion was to continue the lifestyle modification. The patient has hypertension, and renal function tests (RFTs) were found to be normal. He was taking valsartan 240 mg medication, but as per the high BP, the medicine was upgraded to 160 BID and to repeat the RFT after a week.

9 System Evaluation

A questionnaire was developed to evaluate the functionality, usability, reliability, efficiency, maintainability and portability of the system. The sample questionnaire is given in Table 4.

The questionnaire was distributed to different types of users which included medical doctors, nurses, lab technicians, dieticians and patients (Table 5).

The evaluation results of doctors, nurses and patients are shown in Figs. 14, 15 and 16, respectively.

Regarding the functionality of the system, around 88 % of the doctors agreed that the objectives of the system are met; it was able to collect the complete history of patients and was able to identify the patient risks accurately; 12 % of the users were neutral. Around 85 % of the doctors agreed that the system's user interface is good and easy to use. Fifteen percentage of the users were neutral. Eighty-eight percentage of the doctors found the system to be reliable, 4 % were neutral, and 8 % disagree that it is reliable. Eighty-four percentage commented that the system is efficient, while 16 % were neutral. Forty-eight percentage of the doctors commented positively regarding the maintainability of the system, while 52 % of the users were neutral. Twenty percentage agreed that the system is portable, 72 % were neutral, while 8 % disagreed.

In the case of nurse users, 90 % of them agreed that the system functionalities are working accurately, while 10 % of the users remain neutral. Eighty-five percentage of the nurses agreed that the system is easy to learn, and they found it con-

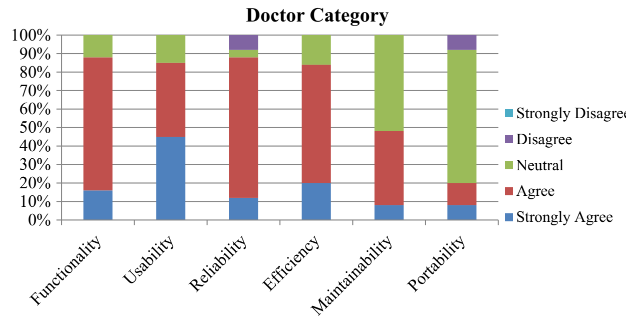


Fig. 14 System evaluation—doctor category

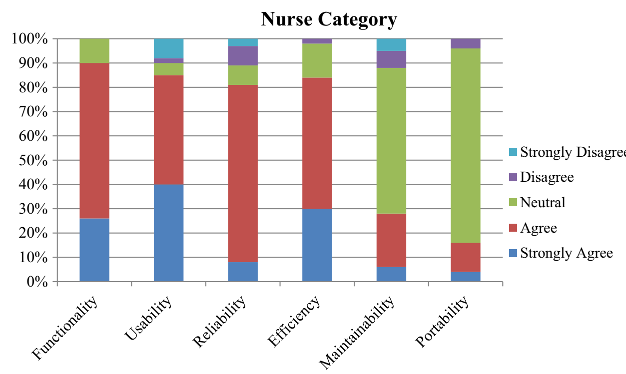


Fig. 15 System evaluation—nurse category

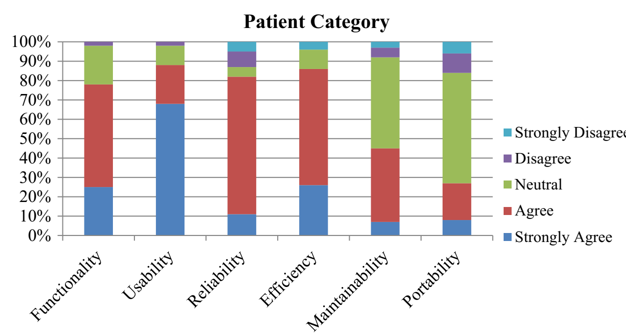


Fig. 16 System evaluation—patient category

fident to use, 5 % were neutral, while 10 % found it difficult to use the system. Eighty-one percentage of the nurses found the system to be reliable, 8 % were neutral, and 11 % disagree that it is reliable. Eighty-four percentage commented that the system is efficient, 14 % were neutral, and 2 % didn't agree that the system is effective. Twenty-eight percentage of the nurses said that the system can store the patient records in a stable manner, 60 % were neutral, and 12 % of the users disagreed regarding the maintainability. Sixteen percentage agreed that the system is portable, 80 % were neutral, while 4 % disagreed.

78 % of the users agreed that the system functions are working fine, 20 % were neutral, 2 % disagreed. 88 % of the patients agreed that the system is easy to use, 10 % were neu-

tral while 2 % found it difficult to use the system. 82 % of the patients found the system to be reliable, 5 % were neutral, and 13 % disagree that it is reliable. 86 % commented that the system is efficient, 10 % were neutral, and 4 % didn't agree that the system is effective. Regarding the system maintainability, 45 % of the patients commented positively, 47 % were neutral, and 8 % of the users commented negatively. 27 % agreed that the system is portable, 57 % were neutral while 16 % disagreed.

In all the three categories, 85–88 % of the users agreed that they are satisfied with the overall system usability. It shows that the system is easy to use.

10 Conclusion and Future Work

In this paper, we presented the ontology design and modeling, implementation of *Process* ontology (clinical guidelines) and the reasoning process of OntoDiabetic CDSS. *Process* ontology is one of the primary ontologies used in OntoDiabetic CDSS. The domain concepts and the guidelines itself are implemented in OWL2 rule language. The reasoner does reason by processing the input (semantic profile) with the stored knowledge (clinical guidelines) so as to reach correct conclusions (risk scores and treatment suggestions). We have used forward chaining inference in our system. The data or facts stored in the knowledge base are matched against conditions of rules in the rule base. The OntoDiabetic system calculates the score and predicts the risk of diabetic patients due to smoking, alcohol, physical activity, sexual and cardiovascular disease that mainly affects diabetes. The system also provides alerts/recommendations and suggests suitable treatments for such diabetic patients having three main complications: post-medical history of the overt cardiovascular disease (CVD), diabetic nephropathy and hypertension. As a future work, tools can be proposed to import the patient details from the existing hospital records or databases. Also, the patient can update the medical problems by sending e-mails, and the system extract the data automatically from the e-mail and update in the semantic profile.

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