Fuzzy HealthIoT Ontology for Comorbidity Treatment

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Abstract. The utilization of Internet of Things (IoT) technologies in the medical field has resulted in the development of numerous intelligent applications and devices for health monitoring. These devices generate a large amount of data, which is collected in various formats and often exhibits uncertainty. As a consequence, interpreting and sharing these data among various medical systems poses a significant challenge. To address this challenge, ontologies, particularly fuzzy ontologies, have been employed to ensure semantic interoperability among these systems and enable them to comprehend, share, and effectively utilize fuzzy data. Therefore, to address these issues, the main objective of this paper is the fuzzification of the HealthIoT ontology. Fuzzification includes concepts related to the medical field and the IoT domain (connected objects). We showcased the application of the Fuzzy-HealthIoT ontology in a specific use case in healthcare, specifically focusing on patient comorbidity management.

Keywords: HealthIoT ontology · Fuzzy health data · Fuzzy ontology · Comorbidity management · Internet of Medical Things

1 Introduction

In recent years, we have witnessed a remarkable technological evolution that has affected various sectors such as industry, agriculture, and education. This advancement has led to a convergence of these fields, giving rise to what is now known as the Internet of Things (IoT) [22]. One particular domain where IoT has made significant strides is the medical sector, leading to the emergence of the Internet of Medical Things (IoMT) [16]. The IoMT refers to the interconnection of medical devices and their integration into healthcare networks to improve service quality [2]. Consequently, numerous heterogeneous systems and medical applications based on connected objects have been developed recently [14,15].

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As a result of the proliferation of Medical Connected Objects (MCOs), a massive amount of heterogeneous data has been generated. These data exhibit semantic heterogeneity as they are acquired in various formats and originate from various MCOs. Moreover, many of these MCOs are mobile, changing their deployment contexts over time based on different criteria such as time and location. This dynamic nature of MCOs implies changes in their descriptions and the data they produce.

These characteristics have presented a complex challenge in the design of interoperable medical systems capable of effectively communicating and exchanging data. To ensure interoperability, it becomes crucial to have a semantic representation of MCOs, their data, and their deployment contexts, which can serve as a unified and shareable model. Ontology has emerged as a promising and efficient solution for explicitly representing IoMT knowledge and relationships.

Although various works have been proposed to address this need [6,18] one significant challenge that has often been overlooked is the uncertainty associated with the received data. In fact, the data captured by the device may exhibit fuzziness due to various factors such as sensor noise, measurement errors, or physiological variations.

For example, when monitoring a patient's heart rate, the device might record values that fluctuate slightly even when the patient is at rest. This variability can stem from factors such as motion artifacts or the device's limitations in capturing precise measurements. As a result, the heart rate data obtained become fuzzy, with imprecise boundaries and uncertain values.

When these fuzzy heart rate data are shared or integrated with other healthcare systems, interoperability challenges emerge. Different systems or platforms may have varying definitions or ranges for heart rate categories (e.g., normal, elevated, or tachycardia). For example, one system may define a heart rate of 90–100 beats per minute as elevated, while another system may define it as normal. This lack of standardized interpretation can hinder effective data exchange, analysis, and decision-making between different devices and healthcare providers.

To overcome these interoperability challenges, a fuzzy ontology tailored to the context of medical IoT can be employed. The fuzzy ontology can capture and represent imprecise data, incorporating fuzzy logic to handle uncertainty and variations [20]. It can define fuzzy sets and membership functions to categorize health data, considering factors such as age, activity level, and individual differences. Using a fuzzy ontology, healthcare systems can achieve a common understanding of fuzzy health data, allowing seamless integration, analysis, and decision support across diverse devices and IoT platforms.

From this perspective, the main objective of this work is summarized as follows.

- We extend the HealthIoT ontology to enable the representation of fuzzy data using the expressive Fuzzy OWL2 language.
- To showcase the practical applicability of our approach, we present a use case study focusing on the comorbidity management. This use case focuses

on predicting heart failure and stroke in patients with multiple diseases, such as cholesterol, hypertension, and diabetes.

– To address this use case, we utilize two distinct datasets obtained from Kaggle. The first data set pertains to heart failure detection[1], which contains 918 samples, while the second data set relates to stroke prediction[2] and contains 1200 samples. The main attributes of these data are summarized as follows.
  - Personal data: this data describes data related to the patient namely: age, sex, work type, residence type, civil situation, smoking_status.
  - Health Properties: contains the different properties specific for each predefined disease such as Resting blood pressure, Cholesterol, Fasting blood sugar, resting electrocardiogram, maximum heart rate, Oldpeak, Body Index Mass, etc.

In fact, comorbidity is characterized by the coexistence of two or more pathological conditions or diseases within the same individual [23]. For example, Long et al. [13] investigated the comorbidity between diabetes and hypertension. Various research studies have also examined the relationship between the comorbidity of COVID and chronic diseases. Kamyshnyi et al. [12] examined the comorbidity of COVID and hypertension, while Guan et al. [10] focused on a patient with cardiovascular disease.

The remaining sections of this paper are structured as follows. In Sect. 2, we provide a motivational scenario to contextualize our work. Section 2.1 outlines the key concepts utilized in our research. Section 2.2 delves into the state-of-the-art in the field. Section 3 presents the extension of the HealthIoT ontology. Subsequently, in Sect. 4, we describe the validation of the Fuzzy Health-IoT ontology. Finally, Sect. 5 concludes the paper.

2 Related Work

In this section, we focus mainly on the state of the art in ontology development in the context of the medical domain. We will first look at deterministic ontologies, and then we will describe the development of fuzzy ontologies.

2.1 Classic Ontologies in the IoMT

Ensuring the semantic interoperability in the IoT and healthcare fields led to various research issues. Elsapagh et al. [5] proposed to extend the SSN ontology in the health domain to present data from mobile objects. They developed an ontological model called FASTO designed for real-time insulin management in patients with Type 1 diabetes. FASTO is based on the high-level BFO ontology, the SSN sensor ontology, and the HL7 FHIR standard. The European Telecommunications Standards Institute (ETSI) has developed an extension of the SAREF ontology for the eHealth Ageing Well domain, known as

[1] https://www.kaggle.com/datasets/fedesoriano/heart-failure-prediction.
[2] https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset.

SAREF4EHAW[3]. This ontology explicitly defines and describes the coupling between components of the IoT domain and the healthcare domain. Its main concepts concern the devices used, the types of communication, the main actors, the measures and the services for the healthcare domain. The authors in [6] have proposed an ontology-based healthcare monitoring system called Do-Care that supports the supervision and follow-up of outdoor and indoor patients suffering from chronic diseases. The developed ontology is a modular and dynamic ontology composed of FOAF, SSN/SOSA and ICNP ontologies with a scalable set of inference rules. The rule bases are dynamic and adjustable to reflect changes in the drug market, medical discoveries, and personal user profiles.

Rhayem et al. [17] have proposed a semantic-enabled and context-aware monitoring system for IoMT. The developed ontology entitled "HealthIoT" represents core domain concepts of the IoT and the healthcare domain. It is based on diverse ontologies such as the SSN ontology, the IoT-lite ontology, time ontology, and so one. Then, this ontology was instantiated with vital signs obtained from medical objects. To exploit and analyze these data 65 SWRL rules are implemented to propose services related to object configuration, disease diagnosis, and notifications proposing.

2.2 Fuzzy Ontologies in the Healthcare Domain

Treating and representing the uncertainty of health data through ontology was taken into account.

Gayathri et al. [8] proposed a fuzzy ontology for activity recognition and temporal information representation(FOAR) using fuzzy logic. This ontology offers enhanced activity recognition through its semantically clear representation and reasoning via fuzzy SWRL rules for aiding activity recognition and abnormality detection for health care.

The authors in [24] proposed a decision support system that allows personalization of imprecise medical knowledge according to the progressive phases of the disease and pathological cases. A rule management process first personalizes the rules according to the specificities of each disease phase and then associates a private knowledge base to each registered patient. This base contains only the patient's personalized knowledge. After reasoning, another customization process is performed by the component, Result Manager, which ensures the validation of the system's results by the experts in case of pathology, before being recommended. The authors in [9] have proposed a type-2 fuzzy ontology for the treatment of depression. This ontology presents data about the medical devices used through the reuse of the sensor ontology and the data related to depression like the mood, the sleep length, the patient's social history, etc. through the depression ontology. A recent study has presented [7] a system that uses a probabilistic ontology to predict the diagnosis of COVID-19, considering the inherent aspects of randomness and incompleteness in knowledge. To incorporate the probabilistic elements into the COVID-19 ontology, a Multi-Entity Bayesian Network is

[3] https://saref.etsi.org/saref4ehaw/v1.1.1/.

employed, enabling robust modeling of uncertainty. The system utilizes probabilistic inference techniques, specifically the Situation-Specific Bayesian Network (SSBN), to facilitate accurate predictions of the diagnosis of COVID-19.

Another study was proposed by Riali et al. [21], have developed a system that integrates fuzzy ontologies and Bayesian networks for the diagnosis of Hepatitis C. The system uses a fuzzy ontology to effectively represent sequences of uncertain and fuzzy patient data. In fact, the system introduces a novel semantic diagnosis process that relies on a fuzzy Bayesian network as its inference engine.

The proposed study in [19] introduced a new approach that integrates hybrid models combining fuzzy logic and Bayesian networks. As part of this approach, the article proposed a language to overcome the limitations of the Probabilistic Ontology Web Language (PR-OWL) when dealing with vague and probabilistic knowledge within ontologies. To validate this proposal, a case study in the medical field, focusing on diabetes diseases, is conducted. In summary, the article offers a solution to enhance ontology-based representation and reasoning in the face of uncertainty using fuzzy multi-entity bayesian networks [11] and demonstrates its effectiveness through a medical case study.

2.3 Synthesis

The aforementioned work has shown promising results in the representation and management of uncertain healthcare data. However, certain shortcomings have been identified in these approaches, such as:

- The fuzzification was mainly focused on health data. There is no work that focuses on data related to medical connected objects.
- All works that use a fuzzy ontology in the medical domain have defined membership functions with the help of domain experts, which is difficult in most cases.

To address these shortcomings, we will focus on fuzzifying the HealthIoT ontology, which combines information related to the medical sector and the IoT domain. The main novelties of the Fuzzy HealthIoT ontology are as follows:

- Fuzzification of concepts related to the medical connected objects.
- Fuzzification of concepts related to the health domain for the management of comorbidities.
- Fuzzification of contextual concepts.
- The use of the DATIL framework and c-means to manage uncertainty in data captured by connected medical objects that are linked to comorbidity management.

To the best of our knowledge, there is no work that addresses the abovementioned aspects in the IoMT.

3 HealthIoT-Ontology Overview

In our previous work [18], a HealthIoT-Ontology was proposed and described. Concepts in the HealthIoT ontology were classified into three categories, namely Medical-Objects Knowledge, Health care knowledge and Context Knowledge as shown in Fig. 1.

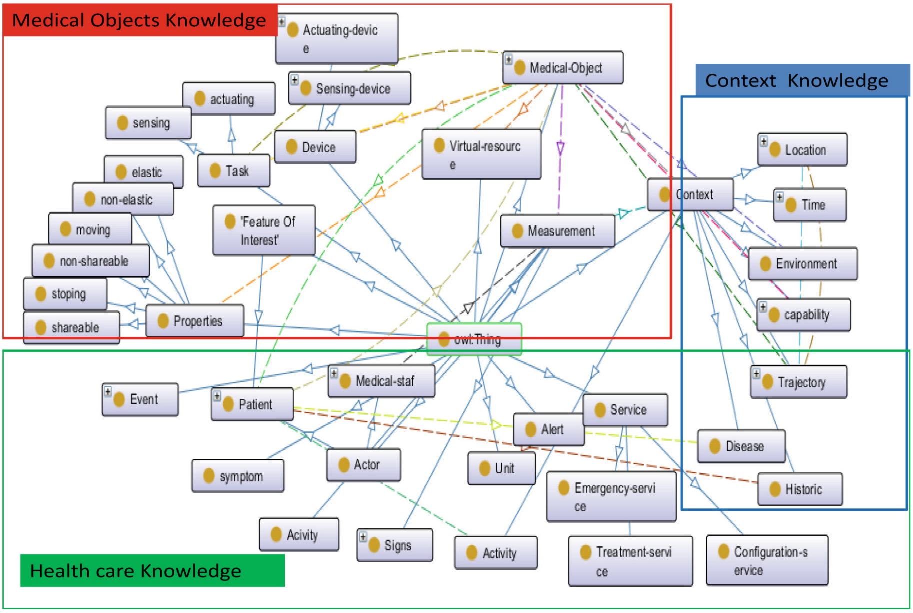

Fig. 1. HealthIoT Ontology Overview.

3.1 Medical Objects Knowledge

In this category, several concepts were proposed to represent the dynamic resources of health data and their relationships. The *Medical Object* concept designed the physical objects that healthcare professionals use to monitor their patients. Diverse objects, defined as instances of this class, such as Withings, Fitbit, scanner, etc. The *Device* class is reused from the SSN ontology [4] to represent the sensors through the sub-class *sensing-device* and the actuators through the subclass *actuating-device*, which is reused from the IoT-lite ontology [3]. In order to define the main task of the Medical object, we proposed the *Task* class that has two subclasses (sensing, actuating). Furthermore, to describe the properties of medical objects such as elastic, non-elastic, shareable, stopping, moving), we suggested the *Property* class. Moreover, to highlight our monitored phenomena, we reused the class *Feature of Interest* from the SSN ontology [4].

3.2 Health Care Knowledge

In this category, we are interested in describing the health care domain by suggesting some concepts as follows.

The *medical staff* class determines the health care professionals (doctor, nurse, surgeon) who maintain continuous monitoring of the patient. This *patient* is a subclass of the feature interest class that refers to the principal and the observed element in this domain. Furthermore, the *Disease*, and the *Treatment* classes were defined to represent the treatment plan for several diseases.

The *emergency service* class provides hospital healthcare service when a critical situation is detected. These diseases can have various health complications. Accordingly, the *Risk* concept is suggested to describe the degree of severity in different contexts. For example, *a diabetic patient with hypertension has a high risk of having heart failure compared to others. The event class was defined to represent the health events that will occur when the obtained health data exceed its threshold.*

3.3 Context Knowledge

To represent the self-adapting requirement of the context-aware IoMT-based system, we defined several concepts as a sub-classes of the *Context* concept. These concepts are classified into two main categories.

The first specifies the deployment contexts of the medical objects. It determines the points crossed by the MCO during a determined period. Therefore, the *Time* class and the *Location* class are proposed to determine the duration of deployment of the medical objects and their position, respectively.

The second category designates the state of the patient. The *disease* concept was proposed to distinguish appropriate actions and treatments. In fact, the treatment plan used by a diabetic patient is different from which is used by a diabetic patient with kidney failure. In addition to that, the *Activity* class is performed to detail the possible activities of the patient and their changes that affect the diagnosis of the disease. For example, an elevated heart rate that is an abnormal event, but it is considered a normal one with a patient in running.

HealthIoT ontology is a crisp ontology, which is limited to represent and resonate precise medical data. Indeed, the membership degrees of all concepts and properties are equal to 1. However, most patient data is vague, especially symptoms, tests, activities, signs, etc.

To meet this challenge, we propose an extension of the HealthIoT ontology. The following section describes the followed process of the fuzzification.

4 Fuzzy HealthIoT-Ontology

The main steps of our development process, as depicted in Fig. 2, will be detailed. Firstly, we will present the proposed fuzzy extension of the HealthIoT ontology, followed by an explanation of how the HealthIoT ontology was adapted to effectively represent comorbidity.

4.1 Step 1: Extending HealthIoT with Stroke and Heart Diseases

This step aims at extending the HealthIoT ontology in order to allow the representation of data on heart failure and stroke. This step is guided by a domain expert and goes through three points:

- **Identify relevant concepts:** In this step, we identify the key concepts that are relevant to representing the heart disease and the stroke. These concepts include specific cardiovascular conditions such as blood glucose level, cholesterol level, body mass index, blood pressure, heart rate.
- **Define Data properties:** Once the relevant concepts have been identified, the next step is to define the data properties within the ontology. The main identified properties from the used data sets are related to the patient and are the age, the gender, the civil situation, etc.
- **Define Object properties:** Object properties establish relationships between different concepts in the ontology.

4.2 Step 2: Fuzzification of HealthIoT Ontology

This step is divided into three main phases as shown in Fig. 2 namely the identification of fuzzy concepts, the fuzzification of the HealthIoT ontology through the DATIL framework, and representing the fuzzy part of the ontology based on additional annotations properties using the Fuzzy OWL 2 plugin[4].

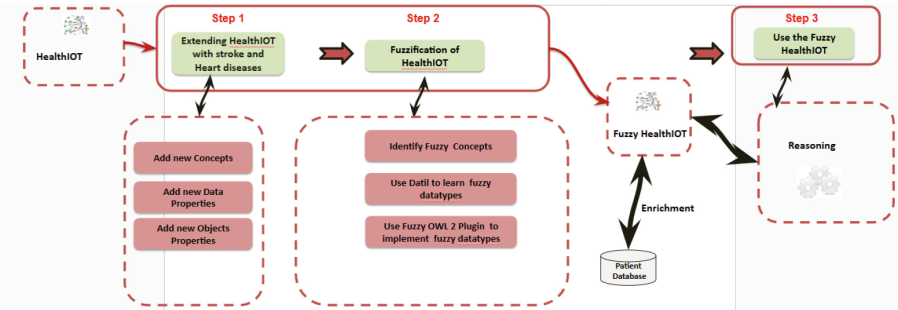

Fig. 2. Proposed process of development

Fuzzification of Patient Data: Diverse information about the patient are fuzzy like the age, and its vital signs such as the glucose level, the temperature level, the blood pressure level among others. The main fuzzy concept that describe this information is the Measurement concept.

[4] https://protegewiki.stanford.edu/wiki/FuzzyOWL2.

Property Concept is about raw data collected from connected medical objects (MCO). It designs the blood pressure (systolic and diastolic), the glycemia, the heart rate, and other vital signs, which are presented as subconcepts of the property concept.

For example, the fuzzy class **BodyMassIndex** can be defined by several subclasses: **LowBMI, NormalBMI and HighBMI**. The class definitions in Description Logic (DL) syntax are as follows:

- **LowBMI**: Represents a collection of BodyMassIndex instances with assigned values of the LowBMI data type, given by the intersection of BodyMassIndex and the existence of the property hasBMI.LowBMI.

$$LowBMI \equiv BodyMassIndex \cap \exists hasBMI.LowBMI$$

- **MediumBMI**: Represents a collection of BodyMassIndex instances with assigned values of the MediumBMI data type, given by the intersection of BodyMassIndex and the existence of the property hasBMI.MediumBMI.

$$MediumBMI \equiv BodyMassIndex \cap \exists hasBMI.MediumBMI$$

- **HighBMI**: Represents a collection of BodyMassIndex instances with assigned values of the HighBMI data type, given by the intersection of BodyMassIndex and the existence of the property hasBMI.HighBMI.

$$HighBMI \equiv BodyMassIndex \cap \exists hasBMI.HighBMI$$

Semantic annotations were applied to all fuzzy data properties, using fuzzy labels, to represent vague knowledge. Membership functions, with the arguments specified in Table 1, were employed to capture the degree of membership. These membership functions were automatically defined using DATIL, and their annotations using fuzzy DL can be observed in Fig. 3.

Fuzzification of Contextual Concepts: In this section, we present some fuzzy contextual information, in particular temporal and spatial contexts.

Time: This concept determines the detection time of the patient's data and the treatment time. For example, doctors prescribe treatment to patients three times a day after each meal. This information is uncertain and imprecise. To represent fuzzy temporal knowledge, we reused the ontology proposed by Nassira et al. [1]. In this work, the authors proposed an ontology called UncertTimeOnto that extends Allen's relations by instantiating them with 13 properties "RelationIntervals, RelationIntervalsCertainty, RelationIntevalPoint, RelationIntervalPointCertainty, RelationPointInterval, RelationPointIntervalCertainty, RelationPoints, RelationPointsCertainty" to present the degree of certainty of temporal indications.

Location: This concept is proposed to represent information about the location of the monitored patient or/and to represent the locations closest to him.

Table 1. Fuzzy Concepts

Fuzzy Concept	Fuzzy Data Property	Sub-concepts	Membership Functions
Patient	Age	YoungPatient OldPatient VeryOldPatient	leftshoulder a = 40.72 b = 53.62 triangular a = 40.72 b = 53.62 c = 64.12 rightshoulder a = 53.62 b = 64.12
Blood-Sugar	hasAvg-glucose-level	LowAvgGlucoseLevel MediumAvgGlucose-Level HighAvgGlucoseLevel	left-shoulder a = 76.37 b = 111.93 triangular a = 76.37 b = 111.93 c = 210.75 right-shoulder a = 111.93 b = 210.75
BodyMass-Index	hasBMI	LowBMI MediumBMI HighBMI	left-shoulder a = 17.11 b = 27.58 triangular a = 17.11 b = 27.58 c = 38.99 right-shoulder a = 27.58 b = 38.99
RestingBlo-odPressure	hasRestingBP	LowRestingBP MediumRestingBP HighRestingBP	leftshoulder a = 115.0 b = 135.46 triangular a = 115.0 b = 135.46 c = 160.96 rightshoulder a = 135.46 b = 160.96
Cholesterol	hasCholesterol	LowCholesterol HighCholesterol MediumCholestterol	leftshoulder a = 1.83 b = 211.3 rightshoulder a = 211.3 b = 297.63 triangular a = 1.83 b = 211.3 c = 297.63
HeartRate	hasMaxHeart-Rate	LowMaxHeartRate MediumMaxHeartRate HighMaxHeartRate	leftshoulder a = 105.19 b = 135.7 triangular a = 105.19 b = 135.7 c = 166.74 rightshoulder a = 135.7 b = 166.74

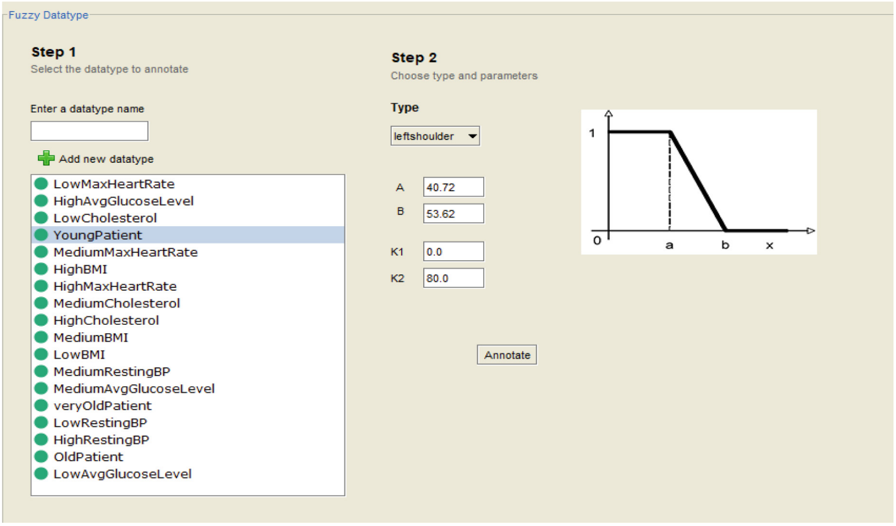

Fig. 3. Fuzzy data types

For example, when a patient has a drop in blood pressure and feels dizzy, his MCO object should send an alert to the nearest hospital. This alert contains detailed information about the location of the patient, as for example “the X patient is actually in the central park that is behind the Carrefour market and he is sitting near the lotus tree”.

In order to model and present this fuzzy and uncertain knowledge, we suggest diverse fuzzy relations that will be assigned between places. In the following table we detail these relations.

Table 2. Fuzzy Location relations.

Approaches	Semantic languages	Domains
Before (l1, l2)	place L1 is before place l2	After (l1, L2)
Behind (l1, l2)	place l1 is behind the place l2	in front-of (l1, l2)
under (l)	under place l	up(l)
near (l1, l2)	place l1 is near to l2	far-away(l1, l2)
at-right(l1, l2)	place l1 is at right of place l2	at left (l1, l2)

Fuzzification of MCO Concepts. This section focuses on the fuzzification of information about connected objects. Indeed, the uncertain concepts are the following:

HIoT:Capability: this concept presents the capabilities of MCO and embedded devices in terms of battery level, battery life, data throughput, etc.

These properties should be presented as fuzzy concepts.

- Battery level can be low, medium, and high. Battery life: expired (if the actual date is higher than the life value), close to expiry (if the actual date is lower than the life value but with a small duration (e.g. 2 days)), and still valid (if the actual date is lower than the life value with a good duration (e.g. 20 days or more)).
- Energy consumption can also be considered as an OMC fuzzy data property. It is estimated by the number of measurements detected during the lifetime of the OMC. For example, if the sum of measurements detected during the lifetime of the object If (sum $<$160) then (energy-state $< -$Strong). If the (sum $>$200) then (state-energy$< -$ Medium). Otherwise, state energy$< -$ Low.

4.3 Validation of Fuzzy-HealthIoT Ontology

To validate our ontology, we propose a process as shown in the following figure. This process consists of three main phases:

- The first step is to collect the data from the medical objects and pre-process them. At this stage, we use OpenRefine[5] software. The main operations are: deleting missing data, modifying the time format, dividing health data into different levels (high, medium, low).
- The second step is the construction of a fuzzy knowledge graph. In this phase, we plan to use the fuzzy HealthIoT ontology and the fuzzy Bayesian network. After that, various rules will be defined for the treatment of comorbidity.
- The final step is to implement a fuzzy medical system that helps doctors and patients obtain appropriate services using SPARQL rules (Fig. 4).

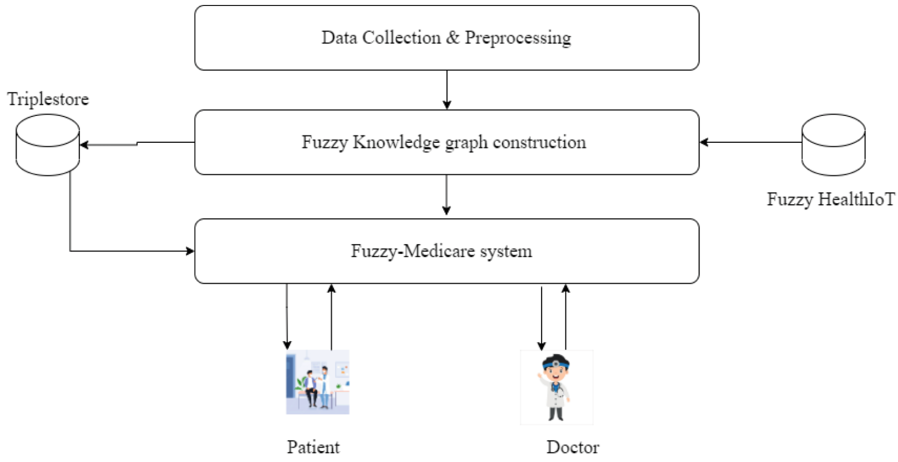

Fig. 4. Validation Process

5 Conclusion

In this article, we have proposed a solution to the challenge of data uncertainty in the context of the Internet of Medical Things. We focus mainly on comorbidity management. In fact, we extend the HealthIoT ontology to represent the complex relationship between heart disease and stroke. Through the use of the DATIL framework, we have proposed a fuzzy extension to the ontology, allowing the incorporation of fuzzy data types learned from real-world data. This fuzzy ontology was implemented using the Fuzzy OWL 2 language.

In future work, we plan to implement the validation process by fuzzy medical system that combines the HealthIoT fuzzy ontology and the fuzzy Bayesian network for the treatment of comorbidities.

[5] https://openrefine.org/.

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