RULE EMBEDDED SEMANTIC ONTOLOGY BASED CLASSIFIERFOR IoTHEALTHCARE

S. Sathyapriya¹, Dr. L. Arockiam²

¹ Research Scholar, Department of Computer Science, St. Joseph's College, Tiruchirappalli, ² Associate Professor, Department of Computer Science, St. Joseph's College, Tiruchirappalli. sathyapriya2822@gmail.com, larockiam@yahoo.co.in

Abstract

Internet of Things (IoT) is an emerging technology in all domains that generates large amounts of data at rapid pace. TheIoT devices are interconnected in a way to communicate and share data with each other. Knowledge mining from such large amounts of data is a difficult task. So commonly, data analytics models reused to extract knowledge. However, most data are not fully utilized because of their dynamic problems and difficulties in analyzing data collected fromdiverse resources. То overcome the above stated issues, semantic technologies are used to provide a common model to handle the data. In the field of healthcare, predicting the patient's disease accurately is one of the most important considerations. For this, semantic data is very useful to make accurate predictions quickly with minimal cost. In this paper, asemantic ontology based technique has beenproposed for IoT based healthcare domain. The proposed technique Rule Embedded Semantic Ontology Classifier (RESOC)is implemented in two steps, namely data collection and semantic enrichment. Data is collected through various sources and then the RESOC is developed in the semantic enrichment phase. Finally, theenriched semantic data enables theDeep neural Network (DNN)for disease classification. The results are compared based on certain parameters such as precision, recall, F-score and accuracy. Hence, the semantically enriched ontology handles heterogeneity and improves classification accuracy.

Keywords: IoT, Semantic, Ontology, Prediction, Healthcare, Analytics.

I. Introduction

Internet of Things (IoT) is a collection of sensing devices that can sense and communicate with each other through internet [1]. These sensing devices have the ability to share and receive information in a variety of applications and offer many services. IoT is one of the most popular internet technologies and has a wider population with real world [2]. Among various applications of IoT, Healthcare domain has driven more attention. IoT technologies provide efficient service to the healthcare domain like monitoring patient, diagnosing, giving treatment, takinga quickdecision, minimizing the cost and avoiding the critical issue[3]. In general, IoT offers we arable devices for patientmonitoring and making decision about the current status of the patient. Nowadays, IoT medical sensors are used widely and it generates big volume of health-relateddata [4]. This data should be analyzed carefully because decisions are very important in the healthcare domain. But one of the major issues in this is data formats, because dataare collected from various sensors and in various sources. So, this will lead to heterogeneity, interoperability and scalability issues [5]. To avoid these issues, semantic web technologies are used toprovide aunique data model for data from various sensors. Normally, it converts the data to meaningful form and explores the structuresand relationshipsbetween the data.

Semantic refers to the meaning of datathat describes the single data in detail manner and it enables better communication by providing interoperability among devices [6]. Ontology plays a key role in semantics because it provides the explanation and characteristics of the data [7]. Another important technology is Resource Description Framework (RDF), it is used to provide a platform for semantic model and it enables the interoperability among various IoT devices [8]. Therefore, this work proposes a semantic based classification model for IoT based health care system. It annotates the datausing rule embedded ontology and returns data in the RDF triple format. Then the semantic information is extracted and given to the classifier that diagnoses the disease accurately.

The remaining part of the paperis as follows, section II explores the existing research works relevant to the proposed work, section III explains the proposed RESOC technique for healthcare domain, Section IV discusses the results of the proposed architecture and Section V provides the results and limitations.

II. Related Works

The related works on IoT based semantic approaches are following,

Gergely Marcell et al., [9]reviewed the semantic sensor technologies in the internet of things. This work reviewed most widely or generally used ontologies in a summarized manner. He also explained layer wise semantic technologies for IoT systems. Finally, the authorconcluded that there was a need for more standardization so as to achieve flexibility, interoperability and quick results.

AhlemRhayem et al., [10] reviewed semantic web technologies in IoT environment. The proposed work reviewed the most relevant research in Semantic Web TechnologiesofIoT domain and summarized list of aspects & drawbacks. Finally, challenges and future opportunities were described.

NouraAlhakbaniet al.,[11]developed the event matching system (SMT) for semantic data in IoT context. The proposed algorithms matched events using a tree-based structure that supports systematic communication among critical applications. SMT was compared with existing work in terms of processing time, from which SMT achieved linear performance time. This system was not suitable for distributed environment and also parallel processing may be applied to improve the processing of event matching.

JoãoMoreiraet al., [12] proposed a SEMIOTICS model for early warning systems in internet of things. The proposedmodel provided semanticinteroperability forIoT systems and discussed some usecases. The model was validated by satisfying the requirements and overcame the challenges which were discussed.

M. Manonmani., [13] reviewed semantic annotation models for healthcare domain. This paper surveyed various data mining techniques which were used in healthcare domain as well as semantic annotation. The survey recommended solutions to overcome interoperability issues in healthcare domain by using semantic annotation models. Also, the steps which were involved in the semantic model creation using feature selection and classification algorithms were explained. This work has not reviewed many semantic annotation models.

SivadiBalakrishna et al., [14]proposed a work for data integration and data analysis using machine learning algorithms for IoT healthcare domain. Various semantic and machine learning techniques for data integration were reviewed. Moreover, future directions were discussed in the field of data integration from sensor in healthcare using semantic and machine learning approaches. The proposed approach for healthcare domain was not implemented using any tools.

T. Elsaleh [15], presented a lightweight IoT stream ontology for annotating streaming data. The model has been developed by following most recognized guidelines of semantic model and IoT environment. Thewell-known Semantic Sensor Networkontology for sensor descriptions was used in the developed light weight model. The annotated data were extracted in RDF Triple format and finally some use cases, tools, application were discussed. Scalability and quick processing were the essential parameters which have to be improved in this work.

Li Chen [16], developed an ontology-based model for diagnosing diabetes, monitoring and giving treatment to diabetes patients in a remote manner. The proposed ontology model solved the

inconsistency problem by analyzing the patient information in detail. The performance of the proposed model was validated using Semantic Web Rule Language (SWRL) rules. Moreover, the experiment results proved that the model well predicted the diabetes disease and recommended prescriptions. The model was not suitable for critical situation because it took more time to process.

III. Methodology

This section proposesmethodology to track and monitor the patients' diseases and prescribe medicine. It includes two important phases, namely, User Module and Semantic Module. In the first phase, physician and patient communicate with each other with the help of IoT devices. The physicians can monitor patients remotely and prescribe medicines anywhere, anytime, without any restrictions. The semantic phase provides several facilities to handle the data from the heterogeneous devices. In semantic module, the dataare convertedinto RDF triple format. For this, rule embedded ontology is developed andis used to merge IoT data with healthcare domain information and find out the hidden relation among them. The semantic module handles the heterogeneity while dealing with various devices and directly interacts with the user module. It covers the semantics with the data by adding self-described information packages. The proposed RESOCtechniquewill handle heterogeneity and improve classification accuracy. The workingflow of the proposed techniqueis shown in Figure 1.

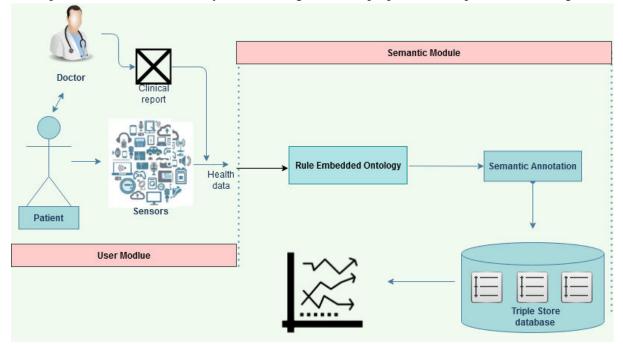


Figure 1: Proposed techniqueforIoT based healthcare domain

A. User Module

The primary role of this module is data collection, where the data arecollected through various methods likesensor mode, questionnaire mode and clinical report. Sensors play a vital role in data collection. There are various types of sensors used such as temperature sensor, heart rate sensor, air sensor, blood pressure sensors, and blood glucose sensor. The personal information collected through the questionnaire contains the details such as age, gender, food habits, heredity disease, height, weight, medicine intake, etc., some details from clinical reports like patient history are also collected. The collected details are sent to the semantic module, where the data is converted into meaningful and understandable format for quick analysis.

B. Semantic module

Thismodule is developed for semantic enrichment of IoT data and semantically enriches data representations. Semantic technologies are applied on the collected data to form the metadata, which includes the environment, the sensor's interpretation, and the configuration to improve knowledge. Eachdata from the devices issent as a token to the semantic module where the rule embedded ontology processes the token and adds descriptions. As discussed earlier, ontology is the key concept of the semantic web that represents well defined knowledge and visualizes semantic descriptions. This phasedevelops rule embedded ontologythat drives semantic knowledge and represents described knowledge as a triple form using RDFgraph, namely subject, predicate and object. Subject denotes resources, object denotes values and predicate indicates the properties or features of the properties and reveals the relationship between subject and object. To develop the rule embedded ontology, basic terms and concepts have to be specified first and grouped into classes, subclasses, object properties and data properties. After that,a set of rules have to be embedded into the ontology. Some of the terminologies of proposed ontology are listed in table 1. Here, Actors are subjects, relations are predicates and concepts are objects.

Table 1: Terminologies for Ontology

Actors			Concepts	Relation
Patient,	Doctor,	Nurse,	Fever, heart attack, treatment,	Has, affected by, treated by, has
Physician,	Staff,	Admin,	blood pressure, high sugar,	symptoms, has value, has
sensors, Manager			disease, eye disease,	tested, has risk, has side effects,
			Temperature, Blood Pressure,	etc.,
			Blood Glucose, air quality, etc.,	

The ontology developed using Protégé 5.0 tool and the pictorial representation of it is shown in figure 2.

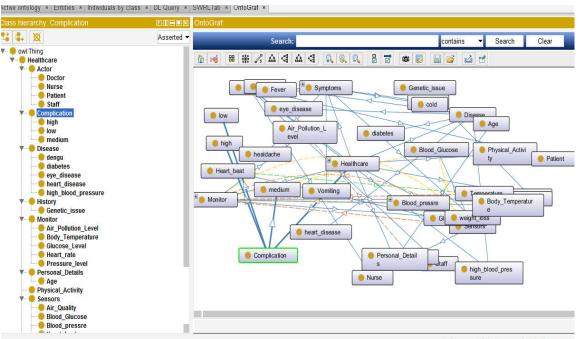


Figure 2: The rule embedded ontology for IoT Healthcare context

Many ontology based solutions are available for healthcare domain, but these are hard to implement with real time decision making. So, the rule embedded ontology is proposed whichperforms well in real time application. Here, the rules are developed using SWRL for finding hidden information from

individuals. Relation and concepts are considered as the primary sources of SWRL because these provide communication between two entities. More than 50 rules are generated based on the concepts of the ontology. Some of the rules are depicted in table 2. These rules play a vital role in semantic reasoning and disease classifications.

Table 2: Rules for ontology in SWRL format

Rules (Written in SWRL)	Descriptions
Patient(?, p)^has	If the value of the temperature is higher than
sensors(?p,temp)^Bodytemperature(?b)^diagnosis(temp	threshold value, then the patient has
, ?b)^has_value(?x,?v)^swrl:greaterThan(? V,	complication highest.
125)->has_Complication (? P, High)	
Patient(?, p) ^has_Symptoms (? P, weight loss)	If the patienthas symptoms of weight loss and
^has_Symptoms (? P, frequent urination)	frequent urination then the patient has diabetes
->has_Diagnosis (? P, Diabetes)	
Patient (?, p) has_booleanvalue (smoking, True)	If the patient has high complication due to the
^has_disease (? P, cough) ->has_Complication (? P,	habit of smoking with cough
High)	
Patient (? ,	If the value of blood pressure is higher than
p)^has_sensors(?p,BP)^BloodPressure(?b)^diagnosis(p	threshold value, and then the patient has
ressureLevel,	complication highest.
?b)^has_value(?x,?v)^swrl:greaterThan(?v,150)->has_	
Complication (?p, High)	
Patient (? ,	If the value of blood sugar is higher than
p)^has_sensors(?p,BloodGlucose)^Gluoces(?b)^diagno	threshold value, and then the patient has
sis(GlucoseLevel,	diabetes.
?b)^has_value(?x,?v)^swrl:greaterThan(?v,350)->has_	
diagnosis (?p,Diabetes)	

Then the Deep neural networks (DNN)classifier is applied to the semantically enriched data for classification. It permits to develop a model and defines its complex sequences in a simpler way. The semantically enriched data with a set of rules are given to the input layer of DNN and net input function X_{in} enables to combine all inputs with corresponding weights as defined in eqn(1). After that, Activation function $F(X_{in})$ is applied to process the inputs to provide the output. The following eqn(1) and (2) explains the construction of the classification model on semantically enriched data.

Let $cx_1....cx_n$ be considered as inputs,

Х

$$u_{\rm in} = \sum_{1}^{n} c x_n w_n \dots eqn(1)$$

The above equ(1) is for computing inputs where, cx and w are inputs and its weights respectively, w provides the information about inputs.

Many Activation Functions are available in DNN. Here, linear activation function is used to process the inputs. It obtains inputs by multiplying w for each neuron and generates an output that is relative to the input vector. The output Y is formed as

 $Y(X) = F(X_{in})$ eqn (2)

The resulting output classifies the diseases. The performance of proposed RESOCtechnique is discussed in the section below.

IV. Evaluation Results:

The proposed technique is evaluated based on parameters such asprecision, recall, F-score and accuracy.For comparison, the raw dataset and the dataset enriched with ontology are considered. To evaluate the performance, the following has to be identified;

TP: True Positive (TP) the quantity of accurately classified the positive labels

TN: True Negative (TN) the quantity of inaccurately classified the positive labels

FP: False Positive (FP) the quantity of accurately classified the negative labels

FN: False Negative (FN) the quantity of inaccurately classified the negative labels

a. Precision for finding the positive classified values from the total number of positive classes, defined as

$$Pre = \frac{TP}{TP + FP}$$

b. Recallalso called as sensitivity, it calculates the positive class labels from the total number of class labels, that defined as

$$\operatorname{Rec} = \frac{TP}{TP + FN}$$

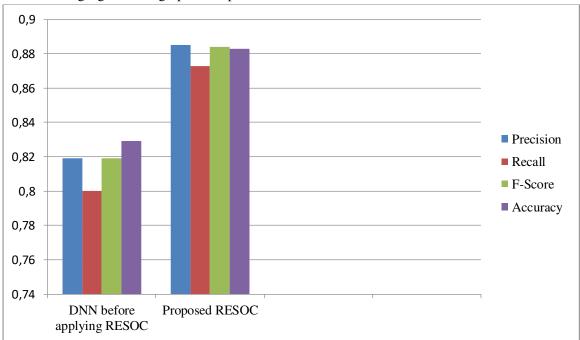
c. F-Score is the harmonic mean of precision and recall

$$F-S = \frac{2(Pre*Rec)}{Pre+Rec}$$

d. Accuracycalculates the value of correct prediction on the dataset,

$$Acc = \frac{TP + TN}{TP + FP + TN + FN}$$

Figure 4 explains the comparative results of the classifier. The proposed RESOC technique enhances the classification accuracy of the DNN classifier. The results are computed based on the parameters that are discussed above. From which, the proposed RESOC technique provides 88% accuracy of the classifier.



The following figure 4is a graphical representation of the evaluation metrics.

Figure 4: Graph representation of the evaluation results of RESOCtechnique Conclusion

In this paper, RESOCtechniqueis proposed for handling IoT based healthcare domain data. The main goal of this work is to solve the heterogeneity problem and to improve classification accuracy. Thistechnique helps the physicians tomonitor the patients anytime, anywhere and at anyplace without any restrictions. It contains two modules, that are user module and semantic module. Data collection is done by various forms in the user module. In Semantic module, rule embedded ontology was developed to enrich the collected data and avoid heterogeneity. The enriched data was then classified using DNNand the performances were evaluated. Thus, the evaluation results prove that the proposed ontology improves the performance of the classifier but processing time is high. In future, the classifier will be enhanced to produce timely results.

References

- [1]. Li, Shancang, Li Da Xu, and Shanshan Zhao, "The internet of things: a survey", *Information Systems Frontiers*, no. 2, Vol. 17, pp: 243-259, 2015.
- [2]. Al-Fuqaha, Ala, Mohsen Guizani, Mehdi Mohammadi, Mohammed Aledhari, and Moussa Ayyash, "Internet of things: A survey on enabling technologies, protocols, and applications" *,IEEE communications surveys & tutorials*, no. 4 , Vol. 17, pp: 2347-2376,2015.
- [3]. Karagiannis, Vasileios, PeriklisChatzimisios, Francisco Vazquez-Gallego, and Jesus Alonso-Zarate, "A survey on application layer protocols for the internet of things", *Transaction on IoT and Cloud computin*, *g*, no. 1, vol. 3, pp: 11-17, 2015.
- [4]. Moustafa, Hassnaa, Eve M. Schooler, Gang Shen, and Sanjana Kamath, "Remote monitoring and medical devices control in eHealth", In 2016 IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), IEEE, pp. 1-8, 2016.
- [5]. Mavrogiorgou, Argyro, AthanasiosKiourtis, KonstantinosPerakis, StamatiosPitsios, and DimosthenisKyriazis,"IoT in healthcare: Achieving interoperability of high-quality data acquired by IoT medical devices", *Sensors*, no. 9, vol. 19, pp: 1-24, 2019.
- [6]. Burzlaff, Fabian, Nils Wilken, Christian Bartelt, and HeinerStuckenschmidt, "Semantic interoperability methods for smart service systems: A survey",*IEEE Transactions on Engineering Management, pp. 1-15,2019.*
- [7]. Seok, Hyun-Seung, and Yong-Ju Lee, "Ontology-based IoT Context Information Modeling and Semantic-based IoT Mashup Services Implementation", *The Journal of the Korea institute of electronic communication sciences*, no. 4, vol.14, pp: 671-678, 2019.
- [8]. Banane, Mouad, and AbdessamadBelangour, "A Survey on RDF Data Store Based on NoSQL Systems for the Semantic Web Applications," In *International Conference on Advanced Intelligent Systems for Sustainable Development*, Springer, Cham, pp. 444-451, 2018.
- [9]. Honti, GergelyMarcell, and Janos Abonyi, "A review of semantic sensor technologies in internet of things architectures", *Complexity*, pp: 1-21, 2019.
- [10]. Rhayem, Ahlem, Mohamed Ben Ahmed Mhiri, and FaiezGargouri, "Semantic Web Technologies for the Internet of Things: Systematic Literature Review", *Internet of Things*, vol.11,pp:1-22, 2020.
- [11]. Noura, Mahda, Amelie Gyrard, Sebastian Heil, and Martin Gaedke, "Automatic knowledge extraction to build semantic web of things applications", *IEEE Internet of Things Journal*, no. 5, vol.6, pp: 8447-8454.
- [12]. Moreira, João LR, Luís Ferreira Pires, and Marten J. van Sinderen, "SEMIoTICS: Semantic Model-Driven Development for IoT Interoperability of Emergency Services", *ISCRAM*, pp:916-973, 2019.

- [13]. Manonmani, M., and Sarojini Balakrishnan, "A Review of Semantic Annotation Models for Analysis of Healthcare Data Based on Data Mining Techniques", In *Emerging Research in Data Engineering Systems and Computer Communications*, Springer, Singapore, vol. 1054, pp. 231-238, 2020.
- [14]. Balakrishna, Sivadi, M. Thirumaran, and Vijender Kumar Solanki, "IoT sensor data integration in healthcare using semantics and machine learning approaches", In *A Handbook of Internet of Things in Biomedical and Cyber Physical System*, Springer, Cham, pp. 275-300, 2020.
- [15]. Elsaleh, Tarek, María Bermudez-Edo, ShirinEnshaeifar, Sahr Thomas Acton, RoonakRezvani, and P. Barnaghi, "IoT-Stream: A Lightweight Ontology for Internet of Things Data Streams", In2019 Global IoT Summit (GIoTS), pp. 1-6, 2019.
- [16]. L. Chen, D. Lu, M. Zhu, M. Muzammal, O. W. Samuel, G. Huang, W. Li, and H. Wu, "Omdp: An ontology-based model for diagnosis and treatment of diabetes patients in remote healthcare systems," *International Journal of Distributed Sensor Networks*, no. 5,vol.15, p. 1–15, 2019