Semantic Interoperability Model in Healthcare Internet of Things Using Healthcare Sign Description Framework

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Abstract: *The healthcare sector has experienced significant technological advances; however, interoperability is one of the biggest challenges. Interoperability in healthcare refers to the capacity to communicate across different healthcare environments. The format, language, syntax, and interpretation of data differ from one healthcare setting to another. Therefore, the lack of interoperability hampers effective communication and data exchange between two healthcare settings. Following the introduction of the Internet of Things (IoT) in healthcare, document-level interoperability is no longer the sole concern; device-level interoperability is also critical. This paper introduces a new Sign Description Framework for healthcare IoT called Healthcare Sign Description Framework (HSDF). Three different signs in healthcare, namely the Vital sign, Medication sign, and Symptom sign, are discussed here. Our proposal demonstrates how interoperability can be achieved using the novel healthcare sign description framework. Implementation of this framework will lead to improved diagnosis and increased cost-effectiveness of treatment.*

Keywords: *Semantic interoperability, healthcare IoT, healthcare sign description framework, ontology, unified medical language system.*

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1. Introduction

Interoperability is the ability of computer systems, software, or intelligent things to communicate and utilize information effectively. For example, the competence of Electronic Health Records (EHRs) and other healthcare data management systems to communicate and share information harmoniously is known as interoperability in healthcare. It is the capacity of various medical applications, gadgets, settings, and service structures to access, coordinate, exchange, and use within and across firms, districts, zonal, national, and international boundaries.

The two major types of interoperability in healthcare are device-level and document-level interoperability. Document-level interoperability work mainly in four categories: 2-layer architecture [3, 7], 3-layer architecture [1, 2], 6-layer architecture [16] and 7-layer architecture [10]. The terms syntax, foundational and technical interoperability are interchangeably used by several authors. Semantic interoperability demonstrates how documents can be transferred from one system to another without affecting the meaning. A medical document may be written on one side in one language and the other side in another. Even if the language used is the same, two systems may use different abbreviations or terminologies. The main issue of document-level semantic interoperability is the absence of an internationally accepted standard format for health records. Some use HL7 [6], others use openEHR [10], and many other caregivers do not follow any format.

Another issue of document–level interoperability is the use of medical terminologies. Some may adopt ICD -10, some may adopt Systemized Nomenclature of Medicine Clinical Terms (SNOMED CT), while others may adopt International Classification of Diseases for Oncology (ICD-O) terminologies. Integrating all these terminologies and different formats into a single umbrella is challenging. [1, 2, 3, 4, 5, 6, 7, 20] semantic interoperability received maximum attention. Most of the research focused on frameworks design, and a few [7, 16, 21] were implemented. To achieve semantic interoperability, [1] adopted ontology methods, [7, 17], adopted agent-based methods, [21] adopted tabular format, and [7, 8] adopted RDF and RDFS was used. Most of the research work in semantic interoperability was done using Ontology Web Language (OWL) and Resource Description Framework Scheme (RDFS). Very little research work has been done on device-level interoperability, and those works were mainly on IEEE 11073 standard.

In [11], a conceptual Interoperability model with seven layers was introduced. In addition, they did a case study for Plug and Play interoperability model with pulse oximeter and infusion pump. According to [11], lower layer interoperability is not helpful for healthcare.

In [20], tabular document representation was used to tackle semantic interoperability issues. In all the above works, linguistic features of the medical documents were not considered. In [8], a multilevel model-driven approach converted Extensible Markup Language (XML) schema to a fully interoperable schema. The system was implemented in RDF, and visualization was done with the help of the Gruff tool. Unfortunately, even though this method was intended for applying the IoT data, the same was not scalable to Internet of Medical Things (IoMT).

According to [21], the Internet collects heterogeneous information. Therefore, they proposed a framework based on a semantic inference scheme and tabular document model to address the heterogeneity problem. The framework was modelled based on, Conex dictionary, rule-based language, and semantic inference algorithm. In [18], a three-layer interoperability framework was proposed. As a case study, they developed two ontologies with the help of Resource Description Framework (RDF)/XML and OWL. However, this framework considered only HL7 and its variants, and failed to represent the integration of different data formats.

For instance, a patient in China suffering from flu visited hospital X, where several laboratory tests and investigations were done. Subsequently, the patient went to India, visited hospital Y submitted the reports of hospital X there. However, since the format used in China was entirely different from the format in hospital Y, they could not interpret the report correctly. This is known as a lack of document-level interoperability.

1.1. Problem Definition

Health information is the heterogeneous collection of unstructured EHR, structured records, and data from various IoT medical devices. The medical document formats, notations, and terminologies used in one EHR are different from another. Likewise, the medical abbreviations, data format, measurement units of the apparatus, and one IoT-Medical Device and terminologies (IoT-MD) are different. Integrating IoT-MD data, structured medical data, and several unstructured EHR data into a unique format is not an easy task. In this model, we aim to design and implement a semantic interoperability model in the healthcare Internet of Things to exchange information inside and outside their organizations seamlessly.

The remaining portions are organized as follows. Sections 2 and 3 describe the proposed healthcare signs and healthcare sign description framework. Architecture is explained in section 4, while sections 5 and 6 depict the Implementation details and results. Section 7 deals with the conclusion of this proposed system.

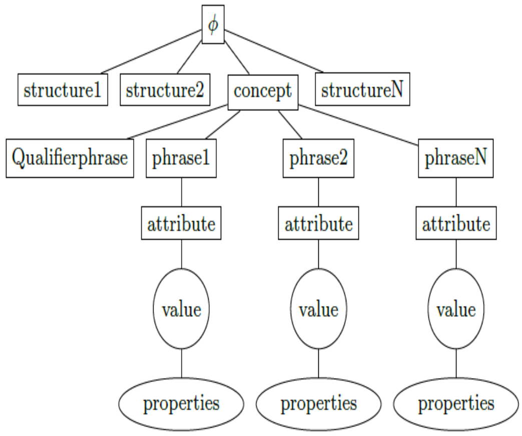


Figure 1. Healthcare sign.

2. Healthcare Sign

Semiotics is the study of signs [12]. A sign is not an abstract entity; it can be an icon, index, or symbol. A sign in healthcare is an object or a value that has physical or virtual existence and may have one or more phrases or may be associated with a concept. e.g., Hyperthermia is a sign that refers to a patient's body temperature that is too high. 113 is another sign that refers to the same Hyperthermia. Here Hyperthermia and 113 are the two different signs of the same concept. Semantic Document Framework (SDF) introduced in [5] contains a root called an identifier. An identifier node connects to two edges called Denotation and Connotation edges. Denotation connects to a vertex called a denotator. Denotator connects to another edge called reification, which connects to a node called reifier.

We have modified SDF for Healthcare Sign Description Framework (HDSF), which identifies as a root node representing the concepts. Concepts always connect to one or more connotation edges which are different structures of the same concepts. Identifier always connects to one or more levels of denotational edges. Level-1 denotator always connects to level-2 denotator and so on. Identifier, denotator, and connotation are signs in SDF. The identifier is a concept generated from the medical document or the data coming from the Healthcare Internet of Things (HIoT) by using the concept processing algorithm represented in [14].

Connotations are the Concept Unique Identifier (CUI) generated for the concepts using the ontology Unified Medical Language System (UMLS) [19], some other medical ontology, program, or computer-generated number. Denotation level 1 phrase can be generated using the Natural Language Tool Kit (NLTK). Each phrase may or may not have some attributes associated with it. If the attribute is a vital sign, there is a value associated with it. Depending upon the value, different properties are assigned.

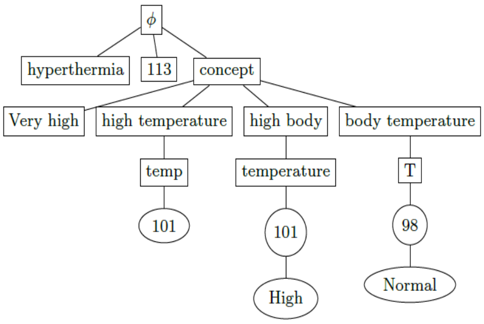


Figure 2. Healthcare sign example.

3. Healthcare Sign Description Framework (HSDF)

Healthcare Sign Description Framework (HSDF) is a bi-type tree [5], consisting of concepts as the root node. As shown in Figure 1, four different nodes are involved in this tree Phrase node, Attribute node, Value node, and Properties node. The Phrase nodes always connect to a concept node and are the children of the concept node. There are three kinds of phrase nodes: Literal phrase node, Qualifier phrase node, and Simple phrase node. Literal phrase nodes are two kinds: In-definitive literal and linguistic literal. Without the qualifier, the In-definitive literal is meaningless. For example, 98OC is a literal associated with the qualifier temperature. The definitive literal has a vital role in healthcare. Linguistic literals are those literals that have no specific meaning in healthcare natural language processing. Depending upon the value of each attribute, five different types of property nodes are assigned low, high, normal, critically low, and critically high. Sometimes some phrases may be associated with some other phrases, as shown in Figure 2.

3.1. Inclusion of Literals in a Sign Description Language

SDF introduced in [5] is not able to accommodate literals. In the healthcare community, these literals have essential meanings. Without literals, most phrases and thus concepts are meaningless.

3.2. Importance of Property Node

Even though there is a standard range of attribute values in the medical field, depending upon the chronic condition, patient under medication, or some other factors, doctors have some set of rules to define the normal and abnormal range of vital values. For instance, if the total WBC count of a chemo dialysis patient is 2.5, it is considered normal by a hematologist.

3.3. Different Categories of Signs in Healthcare

In this section, we have classified healthcare signs into different categories. They are the literal sign, symptom sign, diagnostics sign, medication sign, laboratory-result sign, procedure sign, and administrative sign.

3.3.1. Literal Sign

This sign does not have its existence. Literal signs are usually associated with vital signs and laboratory result signs. E.g., B.P is 100/60.

3.3.2. Symptom Sign

Any phrase may contain one or more medical symptoms. Symptom signs can be classified into the automatic symptom sign and interpreted symptom sign. An automatic symptom is directly observable by the patient or caregiver, e.g., Headache. Interpreted symptom signs cannot be directly observable by a human being; instead, these are derived from the attribute values. E.g., hemophilia can be interpreted by looking at the total W.B.C count of a person.

3.3.3. Diagnostics Sign

This sign is associated with the cause of the symptoms. Even though diagnostics sign also has two categories, automatic and interpreted, the interpreted sign is more accurate. Patient id, timestamp, diagnostics details are the main components in diagnostics signs.

3.3.4. Medication Sign

A doctor's prescription can be regarded as a medication sign. Medication sign usually contains medication name, dosage, route of administration, and frequency.

3.3.5. Vital Sign

The Sign associated with a vital value of a patient. This system considers all measurable parameters such as vital signs, namely temperature, B.P, Pulse, SPO2, and non-measurable parameters like Pain. The format of a vital sign is {patient id, vital name, timestamp, value of the vital}. Attribute description is added at the end if vital signs are augmented.

3.3.6. Procedure Sign

Medical procedures such as intrathecal injection, Anaesthesia procedure, any theatre procedure, chemotherapy, blood transfusion, and radiation procedures are classified as procedure signs. The format is {*patient-id, Timestamp of the procedure, Procedure Name, Procedure details, Site of the procedure, location of the room*}

3.3.7. Laboratory Result Sign

If there are multiple outputs associated with a single laboratory test like Complete Blood Count (CBC), we need to construct separate healthcare signs for each component of the laboratory result.

3.3.8. Administrative Sign

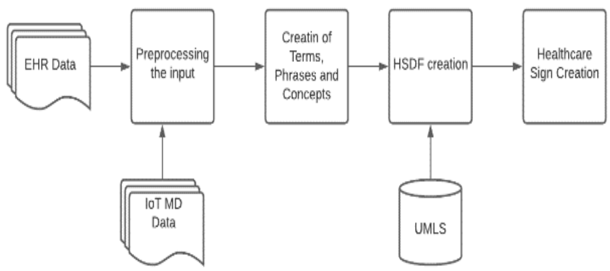
All the non-medical items in the discharge history come under the administrative sign. Registration details, Billing details, patient category, family history, food preference, insurance details come under the administrative sign. Most of them are helpful for insurance companies, and some of them are even useful in diagnosing lifestyle or chronic diseases.

4. Architecture

Figure 3 represents the proposed system, which uses three types of data

1) Input-Data coming from any IoT device (IoTMD)
2) Electronic Health Record (EHR) Data
3) Home collection data.

Since most of the cities in India are offering Telemedicine services, people can collect their data remotely and send it for getting expert advice. Not much processing is required to get the relevant information from IoT-MD data, while second data requires advanced natural language processing. Initially, medical documents underwent steps like tokenization, parsing, and chunking. After parsing the document, relevant keywords such as terms, phrases, and concepts are retrieved with the help of the medical ontology Unified Medical Language System (UMLS) [18]. Word semantics are represented in [ccc]. The Concept Unique Identifier (CUI) of the Metamorphosys file in the UMLS represents each medical concept. In this system, we create three healthcare signs, namely Vital Sign, Medication Sign, and Symptom Sign.



Figurer 3. Architecture.

4.1. Medical Term Identification

All noun phrases are extracted using the noun extraction algorithm represented in [17]. Usually, Nouns are in JJNN, NN, JJJJNN formats. JJ is the tag for adjective, and NN is for the nominal noun. When checking the noun phrases in the MRCONSO table of UMLS, if it receives a CUI, it is a medical concept. STY field of CUI in the Concept table of UMLS (MRCONSO) table of the UMLS Metatheasurus file gives the appropriate category of medical concepts. For example, if Semantic Type (STY) field of Semantic Type table of UMLS (MRSTY) table is “CD,” it is a Clinical Drug, so the String (STR) field of that CUI is a medication. If the semantic category is a symptom or disease, an associated medical concept comes under the symptom or disease category. The procedure list is identified by the terms such as “TPP,” function, a spatial, or diagnostic concept in the semantic field.

4.2. Vital Sign Creation

The data collected from any IoT device is structured and can be processed efficiently. Nevertheless, the vital value present in the medical document has to be extracted. Algorithm (1) represents the Vital Sign Creation process. We created different signs for each vital. The steps to build vital signs are shown below. For processing IoT values, we neglect the first three steps

1. Input EHR of the patient
2. Pre-process EHR
3. Extract Medical terms using UMLS
4. Identify vital name, value, and time of record
5. Convert the vital value to a SI unit
6. Build vital signs using the connotators, denotator, and reifiers.

Algorithm 1: Vital Sign Creation

INPUT: IOT-MD data, EHR Data, Home Collection Data
OUTPUT: Vital Healthcare Sign Description Tree (HSDT)
Initialize Synonyms set ζ to ϕ Cannotor set Γ to ϕ
$\forall$d £ document
  If X £ Sentence in document
  Extract all concepts using concept processing algorithm [13]
  Store it in Set Y
  End if
$\forall\alpha$ £ y
  If α is a vital value
  Find the CUIs of α using UMLS ontology
  End if
$\forall$ CUI £ α
  Do extract Synonyms of CUI (α)
  Add Synonyms of CUI (α) to ζ
$\forall\Gamma$ £ ζ
  mark each Γ as Cannotor mark patientid and timestamp as Denotator
  Mark property of the vital value as Reifier

4.3. Medication Sign Creation

Medication signs can be decoded from the medical document using Algorithm (2). To extract the concepts related to medication, we use both the Metathesarus files and RXNorm Files of UMLS.

4.4. Symptom Signs Creation

If any medical term returns 'sign ' or 'finding' as STY field of MRSTY, it belongs to the symptom list category. Sometimes these symptoms can be an inference of the doctor, or it may be deduced by assessing the test reports. Moreover, some symptoms can be the after effect of some other diseases, or sometimes it may be due to some medications. For, e.g., Neutropenia, nausea, and vomiting can appear as a symptom in patients who took the medication like 6.Mercaptopurine. In such cases, dragonizing the disease is possible by knowing the patient's history. In this work, we have taken only the symptoms directly present in the medical document.

Algorithm 2: Medication Sign Creation

INPUT: A Medication Name
OUTPUT: A-Medication Sign Description Framework
∀α £ Medication Name
Do find the generic name g and add it to set G
if g £ G then
    find CUI(g) and add to set CUIG
end if
∀α £ CUIG
    Do find the synonyms of α and add them to set
∀X £ SUIG do
    Mark X as s connotator of α
    mark denotator as patientid
    mark reifier as dosage, frequency, route of administration,and strength

Algorithm 3: Symptom Sign Creation

INPUT: Medical document with symptom
OUTPUT: Symptom sign description Framework
Identify the symptom category as a prognostic sign, anamnestic sign, Diagnostic sign, or Pathogonomic Sign.
∀α £ Symptom Category findings
    Retrieve all CUI of α
    Add all CUI to set A
∀ζ £ A
    Find all Synonyms of ζ using the MRREL table
    Add Synonyms to set Γ
∀γ £ Γ
    Mark all γ as Connotator
    Mark Patient id, symptom severity, and frequency as denotator
    Mark the category of symptom (prognostic sign, Anamnestic sign, Diagnostic sign, or Pathogonomic Sign) as Reifier

5. Implementation

Implementation of the proposed system is done in Python and UMLS ontology. After obtaining the license from the National Library of Medicine, the UMLS2019AA release is downloaded and it is unzipped to get six different files of size 40.6GB. Metamorphosys and RXNorm files of UMLS are installed and all rich release format files are loaded into MYSQL. Pre-processing the unstructured medical documents is done using the NLTK tool. Creation of the data frame from EXCEL and CSV files are processed using NumPy and pandas module of python. The simple Imputer function of Scikit learn is used to handle all missing values in the dataset using the mean strategy. Plots are created using Matplotlib and Seabourn library of python. Finally, the indexing technique represented in [15] is used to generate the medical signs.

5.1. Observations-Sign or Symptoms

Some medical terms fit into one category, while others fit several semantic categories. For instance, the term Loose Motion returns one and only one CUI C21229214, and it belongs to the sign or symptom semantic category. Conversely, Term Fatigue returns several CUIs and these CUIs belong to different semantic categories. CUI C004095 and C0015674 of the string Fatigue represents Disease or symptom semantic category. CUI C0004304 and C0015676 represent the semantic category of mental process. C0015672 represents the sign or symptom category. The term Vomiting returns five different CUIS, out of which one CUI C0014498 is a disease or syndrome semantic category, four CUIs C0018926, C00020450, C0027498, and C0042963 are a sign or symptom categories. List of ambiguous words are shown in Table 1.

5.2. Observations-Disease

Diseases may fall into disease/syndrome categories or findings. Hypothyroidism returns 2 different CUIs C1830840, C2735554

5.3. Sample Output -Vitals

P1A1| C00005823|B.P |2020-07-21:48: 53| 110| 90 | Normal 2020-07-11| 14:38:54| 120| 80| Normal. Here blood pressure (CUI C00005823) values of two different times of patient with dummy hospital Id P1A1 is represented

5.4. Sample output Medication

161, Paracetamol, 3006, 3143, 42844, 2532, 94236, P1A1, BD, 500mg, oncea month, Oral, 1 month, tablet, P1A1, completed

Table 1. List of ambiguous words.

Word	CUI	Concept	Semantic type
Neutrophil	C0027950	Neutrophil l	Cell
Neutrophil	C0054878	A protein	Protein
Hyperthermia	C0015967	Fever	Symptom
Hyperthermia	C0094505	R Procedure	TPP
Neutrophilia	C0151683	Neutrophilia	Finding
Neutrophilia	C3665444	Neutrophilia	Disorder or Disease
Intrathecal	C0677897	ITRDA	Functional concept
Intrathecal	C1370196	I Space	Body Space
COVID	C4080914	STA device	Medical device

6. Results and Discussion

In this section, we discuss datasets used and obtained results. We have considered three different healthcare signs: vital signs, medication signs, and symptom signs. We have considered structured, unstructured, and IoT-Data. Dataset -1 is the Pima Diabetic dataset

[13] of size 250kB, Dataset2 is the IoT-Monitoring dataset of size 450kB from the machine Philip's intellivue collected from Aster Medcity Kochi, Kerala, India. Dataset-3 is theCOVID-19 Dataset of size 700kB, Dataset-4 is the thyroid dataset of size 950kB from the UCI repository, and Dataset-5 is the electronic health records of size 1.1MB. First and fourth datasets are purely structured, while the EHR data set is unstructured. The covid dataset contains both structured and unstructured data.

Table 2 represents the sample monitoring data of a patient admitted to ICU of Aster Medicity Kochi Kerala. The data is collected from the Philips Intellivue machine. The main components in the monitoring data are vital signs, medications administered, food intake, and urine output. Vital values include SPO2, EtCo2, temperature, heart rate, pulse rate, arterial BP, and respiration rate. Medicine intake contains medicine name, quantity, and route of administration. Food intake contains food in grams and type of intake. We have created three JSON files, one for vitals, one for medication, and the third for food intake and urine output.

Table 2. Sample monitoring data.

Age(ADT) 5 years	**Allergies-No Known Drug Allergies**			
04-08-2018	**10.15**	**10.30**	**10.45**	**11.00**
Fentanyl 15mcg	30			
Midazolam 0.7mg	0.7			
Propofol 10mg	10			
Vecuronium 5mg	2			
Glycopyrroiate 0.1mg	0.1			
Paracetamol 0.5mg				
O2	4			
SPO2			99	87
EtCO2			4	3.8
Temperature (C)	98.7		99	

6.1. Evaluation Measures

Interoperability means similarity among different systems. So, in this study, we took the similarity between one document and its corresponding HSDF. We considered cosine similarity to calculate the similarity. In cosine similarity, documents and nodes of the tree are represented as vectors of relevant medical terms vector (V1) and vector (V2), respectively. If both V1 and V2 are highly similar, their dot product is one, and the angle between the two vectors is zero. If the angle between them is 90, vectors are highly dissimilar.

Many healthcare frameworks are built corresponding to a single healthcare document in most cases. So, we took a summation of the healthcare framework to calculate the similarity. The intention of taking cosine similarity between the health record and HSDF is to determine whether all concepts in the medical records are also represented in HSDF. One sample of generated HSDF is shown in Figure 4.

$$Similarity(\overrightarrow{DocA}, \overrightarrow{HSDFA}) = \frac{DocA\,.HSDFA}{|DocA||HSDFA|} \quad (1)$$

$$= \frac{\sum_{i=1}^{n}(DocAi)(HSDFAi)}{\sqrt{\sum_{i=1}^{n} DOCAi}\sqrt{\sum_{i=1}^{n} HSDFAi}} \quad (2)$$

$$HSDFAi = \sum_{j=1}^{m} HSDFA_i^j \quad (3)$$

The thyroid dataset from the UCI repository contains two documents, one for hypothyroidism patients and the other for hyperthyroidism patients. There are three HSDFs associated with each document of the thyroid dataset. The cosine similarity between document1 of the thyroid dataset and generated HSDFs is 0.923, and the same between the second document of the thyroid dataset and generated HSDFs is 0.942. The average cosine similarity of the thyroid dataset is 0.9325. The covid dataset contains two documents. One document is an EHR file; another is an IoT-MD home collection data file. The cosine similarity of the IoT-MD Covid dataset is 0.983, and that of the EHR dataset is 0.89. The average similarity of the covid dataset is 0.9365. Pima Diabetic database contains only a single document and got a similarity of 0.943. The fifth one is the IoT-MD dataset of patients admitted to ICU. The cosine similarity of all documents in IoT-MD data with generated HSDFs is above 90%, and the average similarity is 95%. From the obtained result, we can conclude that cosine similarity is high for IoT-MD data, same is low for unstructured.

The intention of selecting Recall, Precision, and F measures is to identify all the medical concepts correctly represented in the healthcare sign description Framework. A sample precision, recall F1-score bar plot is shown in Figure 5. The intention of selecting Recall, Precision, and F measures is to identify all the medical concepts that are correctly represented in the healthcare sign description Framework. A sample precision, recall F1-score bar plot is shown in Figure 5.

$$precision = \frac{TSM}{TSM+NMS} \quad (4)$$

$$\text{Recall} = \frac{\text{NM}}{\text{TSM} + \text{NMS}} \quad (5)$$

TSM is the number of correct medical terms selected. NMS is the number of non-medical terms selected. NMNR is the number of non-medical terms which are not selected. MS is the number of medical terms which are not selected. NM is the total number of medical terms. Precision is the ratio of the number of medical terms correctly identified and the number of terms selected. The recall is a ratio of the number of medical terms correctly identified and the number of medical terms present in the document. Obtained confusion matrix for identifying the medical and nonmedical terms of EHR health data is represented in Figure 6. The confusion matrix for three medical terms of IoTMD-data is represented in Figure 7.

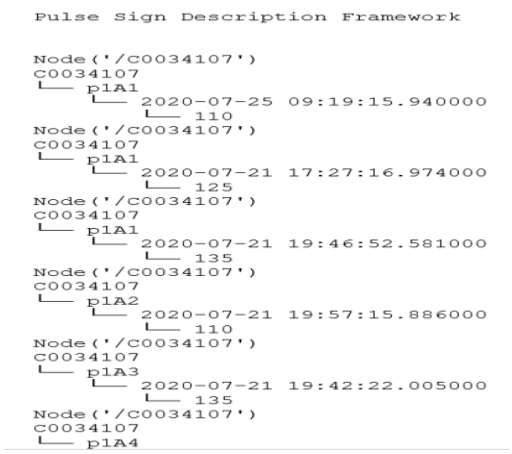


Figure 4. Sample HSDF.

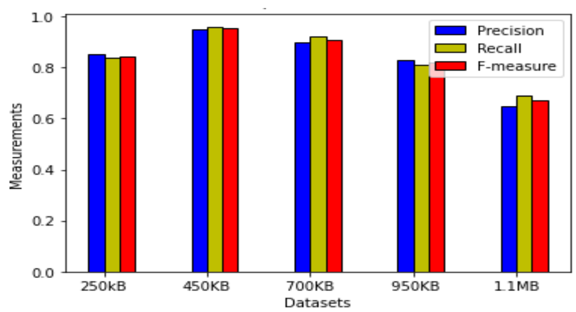


Figure 5. Precision, recall, F1-Score of vital sign.

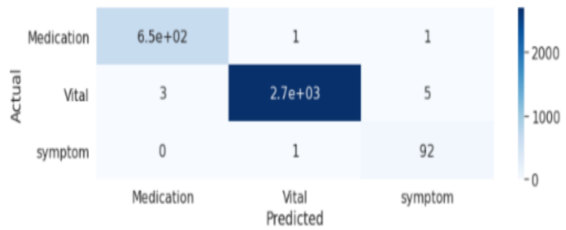


Figure 6. Confusion matrix of three healthcare signs.

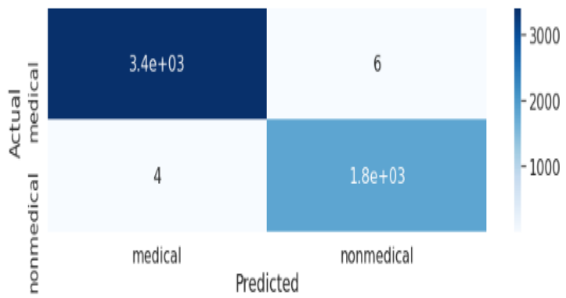


Figure 7. Confusion matrix for medical and non-medical terms.

7. Conclusions

In this paper, we have presented a healthcare sign description framework called HSDF. Three health signs (vital signs, medication signs, and symptom signs) and corresponding three algorithms are designed. These signs are used to solve semantic interoperability problems in the healthcare field. We have evaluated the proposed model using cosine similarities between healthcare documents and generated HSDF. The IoT-MD dataset performed well while the accuracy with the unstructured data was significantly lower. With the use of medical concepts extracted from the UMLS ontology, linguistic challenges such as synonymy, meronymy, holonomy, and word sense disambiguation problems are avoided, and accuracy and similarity are enhanced. Using HSDF, a document transferred from one healthcare setting to another can be easily interpreted by the other. Therefore, repetition of investigations and tests already performed earlier can be avoided or reduced, thus resulting in the cost-effectiveness of treatment.

As we progress with our research, we would like to extend the scope of this research to include remaining healthcare signs. This method can also be applied to create healthcare image signs so that caregivers can seamlessly identify the location, type, and strength of the deformities present in the images. In addition, some optimization techniques can be employed to optimize the generated framework to reduce the size complexity of the generated HSDF.

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