Schema Ontology Model to Support Semantic Interoperability in Healthcare Applications: Use Case of Depressive Disorder

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Abstract— The provision of semantic interoperability among heterogeneous data is important issue to cope with a tremendous potential of diverse healthcare applications. This paper describes schema ontology models to support semantic interoperability in healthcare applications of depressive disorder (DD) using the framework of Web of Objects (WoO). And the implementation aspects of semantics interoperability with required schema ontology models and their integrated associations are defined to characterize the target interoperable ontology of affective DD states.

Keywords— *Depressive Disorder; Healthcare; IoT; Ontology, Semantic Interoperability; WoO.*

I. INTRODUCTION

Data interoperability benefits the global healthcare market, which is increasing with tremendous potential for diverse applications. These application areas include healthcare systems, diagnosis and consultation applications, telehealth solutions, clinical decision support systems, health information interchange applications, chronic healthcare management applications, and several others.

Moreover, healthcare services are not only restricted to stationary information services but they have evolved into more dynamic applications, such as remote health monitoring in pervasive and Internet of Things (IoT) enabled environments, such as emotion detection, depressive disorder analysis [5][6], or mental health monitoring from physiological signals collected through smart sensors. However, in these type of applications, data interoperability still poses a major challenge. Applications that provide healthcare services by monitoring the affective human health state, such as emotions, collect data from diverse heterogeneous sources and modalities using wearable and stationary sensors and devices, as well as from smartphones.

In such applications, heterogeneity in data models, data processing methods, and communication protocols develop interoperability bottleneck and limit the integration of data collected from multiple sources and reduces the flexibility for healthcare information sharing in smart environments. The proposed Functional Model of Semantic Data Interoperability (FMSI) supports the semantic interoperability provision in three ways that are the semantic level, syntactic level and object abstraction level. FMSI generalizes the mechanism to support semantic interoperability among different domains. Semantic mediation function of FMSI offers the mechanisms for semantic translation and linking of the data from different platform, which involves semantic vocab description maintenance, semantic translation and annotation, and semantic alignment and validation functionalities.

II. FUNCTIONAL MODELS FOR SEMANTIIC DATA INTEROPERABUILITY

One of the major challenges that various platforms are facing is the heterogeneity of data and resources which hinders the interoperable sharing and reuse. Existing system suffer from many obstacles to completely achieve interoperability at data level. To overcome these challenges, the proposed work contributes to a semantic ontology model and provides a solution for data interoperability in heterogeneous healthcare applications. The model involves several features including the semantic annotation of healthcare data collected from different sources, a semantic alignment mechanism involving the deep representation learning, and the integration of healthcare concepts. The work also contributes a base ontology model to provide the mapping of healthcare concepts from diverse ontologies. It provides a Web of Objects (WoO) based ontology catalog infrastructure [1][2][8] to deploy semantic ontologies which could be utilized by diverse healthcare systems to support interoperable data management and processing.

A. Semantic Ontology Association using Web Objcts

In semantic interoperability provisioning, the semantic alignment and linking functional features to support the semantic sharing of information in an efficient way. To provision the semantic interoperability with mechanism of generalized alignment within source and target ontology models the functional components are developed using CVOs and microservices based on Figure 1.

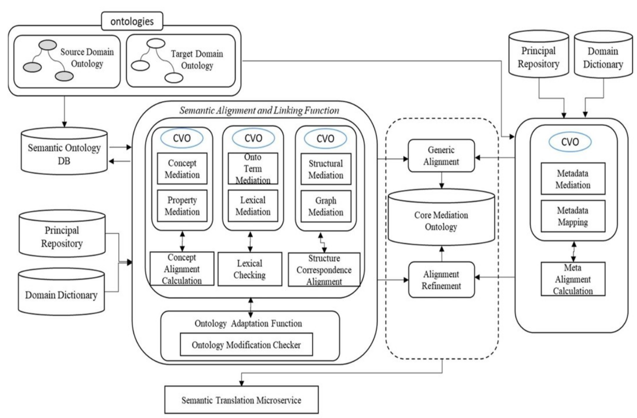

Figure 1. Semantic association functional features interaction

As indicated in Figure 1, semantic ontology association function manages the change over the ontologies in the association process. It maintains the initial status of ontologies and the after algorithm modified ontology model. Also, semantic interoperability requires the interoperable machine readable format to retrieve and process the ontology information for this purpose semantic ontology repository has been considered. The domain dictionaries have been considered such as WordNet dictionary to provide lexical resource in the alignment process. Additional to the semantic data interoperability features, the metadata interoperability has been considered as the vital feature to enhance alignment in the ontology mapping.

B. Semantic Base Ontology Model using WoO

The semantic base ontology consists of the generic concepts to support the semantic interoperability for healthcare applications. It includes the base object entity which represents a Real World Object (RWO). The RWO has the operation mode as it may represent any sensor or actuator, however if the RWO represents any other information this mode will be set to none. A Base Object Element (BOE) is an entity to hold a base object. The BOE can have input features as well as the output features. Each feature has associated metadata with it which presents the details on the BOEs and the operation that can be supported on this abstraction. The Composite Elements (CE) are the entities in the base ontology that will contain the collection of BOE entities. They have also features and the associated metadata. Base Ontology model have interface to the standard W3C SSN ontology and other external ontologies to express and provide interoperable features with existing systems.

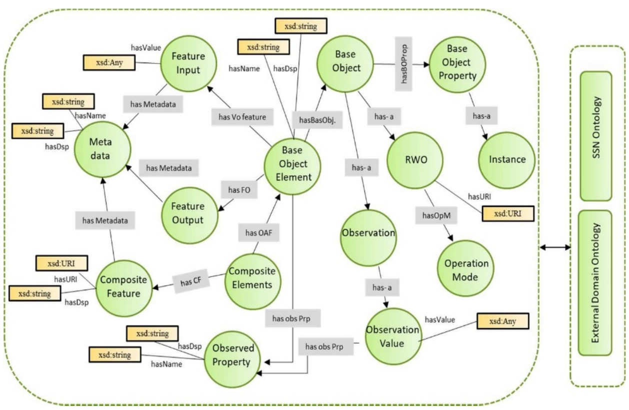

Figure 2. Base Ontology Model [4]

C. Core Mdiation Ontology(CMO) Model using WoO

Core Mediation Ontology (CMO) is a mediation design pattern that provides an alignment and arbitration for source and target ontologies. The CMO includes mediation concept which is sub categorized into core data concepts and structure concepts. The core data mediation concepts include, core data mediation, metadata mediation, features mediation, source feature mediation, object mediation, data property mediation, range mediation and domain mediation. These concepts are used to express the alignment through specific algorithm based on the used formats. The CMO also contains the concepts related with the structural mediation among the ontologies to be aligned. From the structural point of view the CMO has mediation concepts like, structure concept, list of aligned sequence, and list of expected match sequence, core domain list, core range list, source sequence concepts, and target sequence concepts.

D. Alignment Mdel to Support Semantic Mediation

To express an example of semantic interoperability mediation, the Figure 4 shows two information models, J and K which provide information about two different systems, and both follow the base ontology model. As both model express arm concept and their features in slight different ways. To enable semantic interoperability among both systems semantic alignment is required. Figure 46 shows the code for the semantic alignment with two defined rules the first provides the equivalence of body arm concept to arm and the second describe the relationship has status from the model J is same as is on status in model k. Following the specified mapping the SPARQL queries are modified in the excerpt of Figure 5.

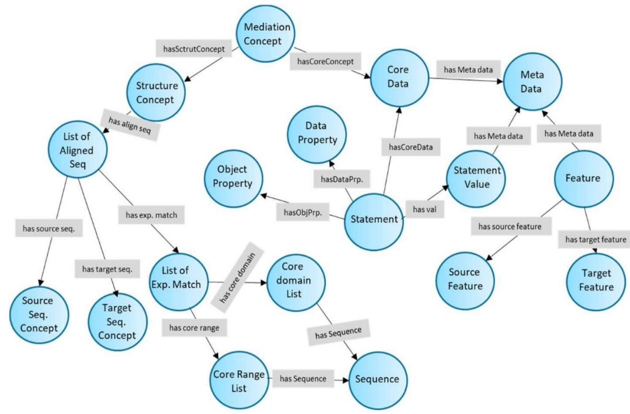

Figure 3. Core Mediation Ontology Model

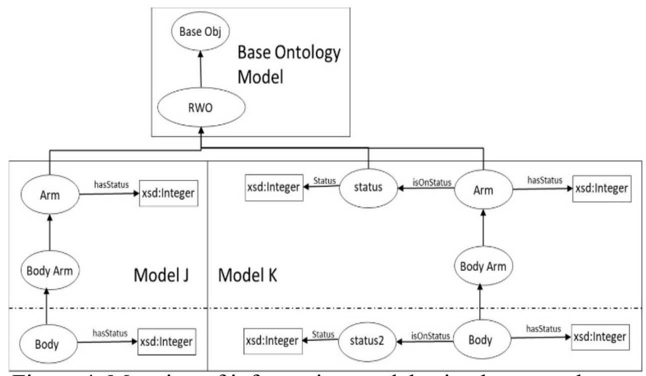

Figure 4. Mapping of information model using base ontology

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@prefix : <http://Semanticweb.WoO.org/Interoperability/Improvedalignment#>
@prefix woohs: <http://woo.anlab.org/woohs/1.0/#>
@prefix modelJ: <http://www.anlab.org/semantic_ontologyJ#>
@prefix modelK: <http://www.anlab.org/semantic_ontologyK#>
@prefix xsd: <http://www.w3.org/2001/XMLSchema#>

<http://www.anlab.org/semantic_mappings/plJ-plK#RuleA> a :Cell ;
:conceptEntity1 modelJ:BodyArm;
:conceptEntity2 [ a woohs:Class ;
woohs:and ( modelK:healthNote [ a woohs:AttributeValueRestriction ;
woohs:onAttribute modelB:Arm ;
woohs:comparator woohs:equals ;
woohs:value [ a woohs:Literal ;
woohs:string "true" ;
woohs:type "http://www.w3.org/2001/XMLSchema#boolean" ] ] ) ] ;
:measure "1.0"^^xsd:float ;
:relation "Equivalence" .

<http://www.anlab.org/semantic_mappings/plJ-plK#RuleB> a :Cell ;
:entity1 modelJ:hasState ;
:entity2 [ a woohs:Property ;
woohs:compose ( modelB:isOnState modelB:State ) ] ;
:measure "1.0"^^xsd:float ;
:relation "Equivalence" .
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Figure 5. Mapping Rules defined using SPARQL

E. Semantic Alignment Ontology Model Using Deep Learning

It provides semantic interoperability based on deep representation learning of ontologies which constitutes two steps as shown in Figure 6, first we generate representations from the ontology graphs using deep learning method and provide the semantic alignment. Secondly we perform alignment using the semantic association algorithm which considers the alignment based on the ontology graph structure. We combine the results of both alignments and perform semantic interoperability checking and then provide the final semantic interoperability provisioning.

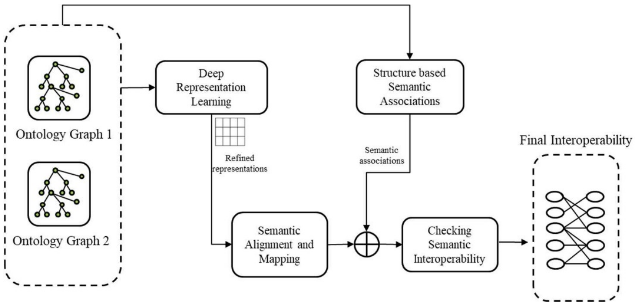

Figure 6. Deep semantic interoperability provisioning process

F. *Enahnced Alignment based on Composite Matrix Learning*

To provide the interoperability using semantic alignment process we have presented a composite approach based on the learning algorithm as shown in Figure 7. In this model after processing ontologies and calculating all alignment measures we build the alignment matrix. This matrix and the actual alignments calculated are fed as input to the learning model. The learning model is based on the classifier which is trained through the provided ontology inputs. The classifier is also tested on the new data based on the ontology similarity matrix. Through the learning based approach a change in the data model is adaptively detected and semantic alignment is processed to provide interoperability among two heterogeneous domain models that are provided as the source and target models.

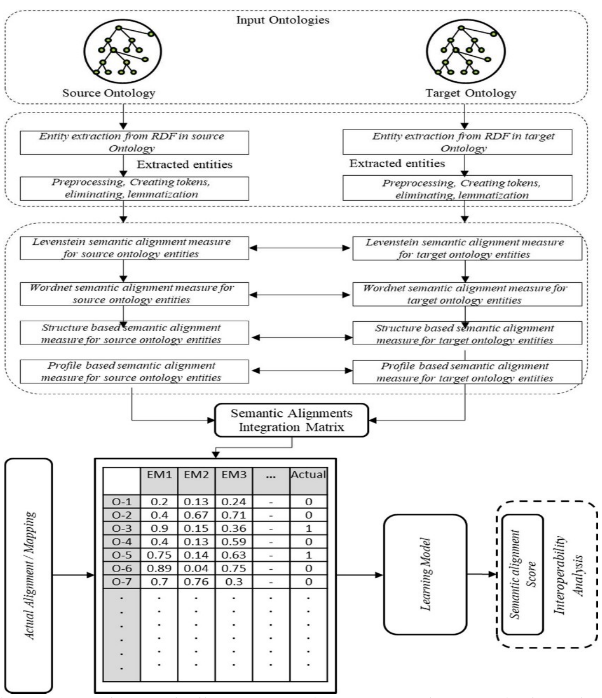

Figure 7. Enhanced alignment using composite matrix learning

III. Semantic Alignment of WoO enabled Depressive Disorder (DD) Ontology Models for Interoprability

The semantic alignment process of DD ontologies has been developed to align the ontology models expressing the healthcare data with the semantic heterogeneity in term of the concepts of the domain and data or object properties of the domain. The alignment has been performed with microservice processes [5] which harmonize the concept from each domain ontologies, in our use case these include AMIGOS ontology [9], DEAP ontology [10] and ACGM ontology model [4]. Microservices extract the ontology concepts in to the list of VOs, which represent the data expressed by individual ontology. Three microservices, each aligning the ontology of individual model to the base ontology model have been developed. Semantic alignment process has been illustrated in Figure 8. The process involves mapping the concepts of semantic model of diverse ontologies into a base ontology model. As indicated in [4], the VO_BVP_d and VO_EMG_d from DEAP ontology model and VO_BVP_A and VO_EMG_A from ACGM ontology model express same type of data with different semantics. The alignment of such data has been achieved using microservices which map these input data based on the semantic similarity processing into common model of base ontology instances.

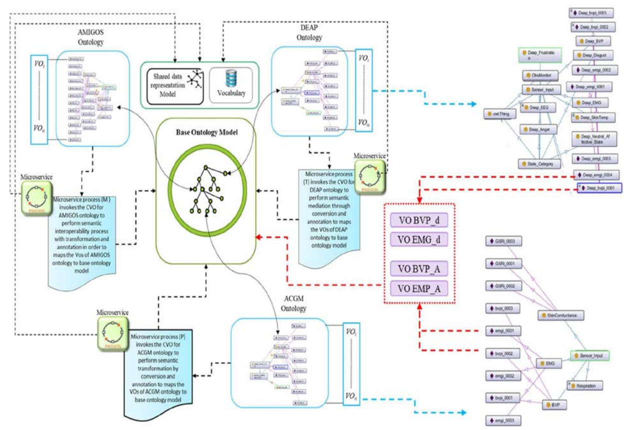

Figure 8. Semantic alignment of ontology models using WoO for DD

Moreover, to support the interoperability of these different annotation schemes of DD ontologies, a common annotation based on the base ontology model has been developed. In this case to map the annotation of the AMIGOS model to DEAP model, a semantic annotation to base ontology model through shared data mapping has been performed.

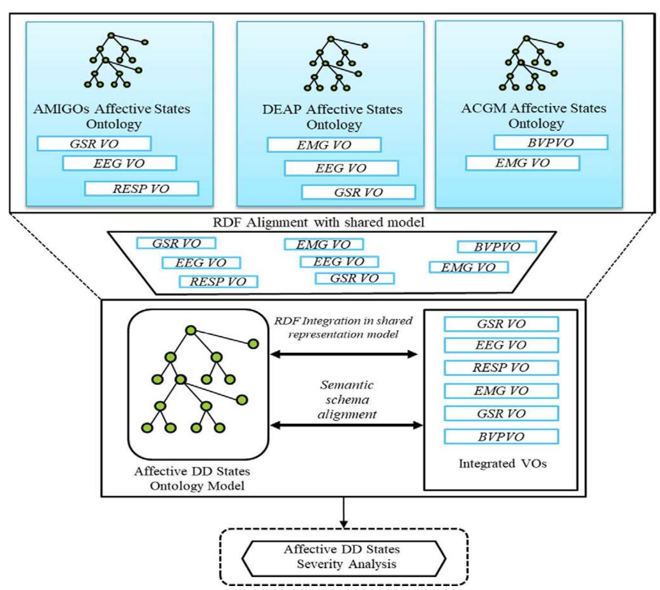

Figure 9. RDF integration based on shared data model for DD

To facilitate the requirements of semantic interoperability, experiments have been performed utilizing the shared data model of interoperable object abstractions. The integration of data from heterogeneous information along with their schema representations have been harmonized in the shared representations. The mechanism has been developed to integrate and express the data in a unique shared data model. Based on the shared representations we have performed analytics through a deep learning model. The processing steps of evaluation has been performed in accordance with the FMSIs described in the clause of III. Of this paper. The framework of Web of Objects [8] has been used to express data and perform its extraction and processing for VO level functionalities and CVO level to define the learning model. As illustrated in Figure 9, data from three different sources are integrated to affective DD states ontology model using RDF alignment and semantic schema alignment.

IV. Conclusion

The paper provides schema ontology models to support semantic interoperability aspects and the functional model of data interoperability provisioning. The deep semantic data interoperability provision on the learning based approaches have been discussed and the details on the step wise process have been introduced. Also, the implementation aspects of semantics interoperability with required schema ontology models and their integrated associations to define a target affective DD states ontology have been furnished in terms of design principles. In the implementation of these associations the provision of microservices representation model and generic model is proposed to support interoperability provision with WoO features. To validate the proposed approach for the schema ontology models for WoO based DD healthcare application, several deep learning settings will be investigated.

Acknowledgment

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