Stroke Medical Ontology for Supporting AI-based Stroke Prediction System using Bio-Signals

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***Abstract*—** In this paper, we propose a stroke medical ontology that provides medical knowledge to accompany AI-based stroke disease prediction system's results that were arrived at based on EMG information. This system was developed as a result of the limitations mentioned above being encountered in previous studies. We approached the problem from a viewpoint of knowledge engineering with the aim of modeling medical knowledge related to strokes. Using web ontology language (OWL), a standard ontology language, we developed schema-level stroke ontologies with concepts and properties based on the brain's anatomical structures, lesions, and disease related to strokes. Also, we developed an instance-level medical terms ontology that can span standard medical terms such as those in the international classification diseases (ICD), systematized nomenclature of medicine - clinical terms (SNOMED-CT), and foundational model of anatomy (FMA). The above schema ontology and instance ontology are meaningfully mapped to each other to apply layered ontology modeling techniques that separate schemas from instances. Through semantic web rule language (SWRL)-based inference, we predict lesions, diseases, and anatomical brain structural ripple effects based on the patient's current lesions and diseases. The inferred knowledge information is provided via the SPARQL protocol and RDF query language (SPARQL), a standard ontology query language. To verify the stroke medical ontology proposed in this paper, we developed an ontology-based stroke disease prediction system. This system achieved knowledge augmentation performance of 67.82% by comparing the patients' current lesions and diseases with the lesions, diseases, and areas of disability found by SWRL-based inference using actual stroke emergency data from 37 patients.

Keywords*— *stroke medical ontology; ontology; SWRL-based inference; stroke; mini stroke

I. Introduction

Stroke is a disease that occurs in the brain and can affect all body organs [1]. Strokes are the result of either cerebral infarction or cerebral hemorrhage [1]. More than 66% of stroke patients die immediately after the stroke or suffer from severe disabilities as a result [2]. One precursor symptom before a stroke occurs is transient ischemic attack (TIA), is also known as a mini-stroke [3]. A *mini-stroke* is an event that is recovered from within 24 hours of what is a temporary cerebrovascular blockage occurring [3]. Mini-strokes are recovered from immediately after experiencing symptoms, thus are often dismissed without recognition. However, 5-10% of patients who have experienced a mini-stroke develop a cerebral infarction later in life [3]. The best method for preventing a stroke is to predict a mini-stroke situation in a timely manner and provide an emergency alarm to the user so they can receive the appropriate medical treatment by being taken to a hospital.

Motivated by this situation, many studies are underway to predict strokes that use modern AI technology for rapid predictions [4][5]. There are many studies on stroke prediction through clinical data and medical image analysis [5]. Besides these, deep learning has shown promising results in various fields and shows exceptional performance at predicting diseases through voice recognition and medical image and video analysis [6][7]. Thus, this technology's usability is rapidly increasing. We developed a stroke prediction system based on machine learning and deep learning, it uses real-time EMG bio-signal data and has developed prediction models with an accuracy of 98.958% when using a deep learning long short-term memory (LSTM) method and of 90.38% when using a machine learning random forest algorithm [7].

However, conventional machine learning and deep learning prediction methods only provide discrete prediction results based on numerical probabilities via a classification or regression method. With just these kinds of predicted results, there is no medical justification for the results to provide doctors or patients with. Furthermore, failure to provide patients with predictive results including some medical knowledge of their condition may result in the patient not fully understanding their dangerous current situation. It is necessary to provide patients with predictive information about their medical situation, this could include the cerebral vessel's location due to an expected hemorrhage or infarction, affected brain portions, expected lesions, and expected diseases.

This paper proposes the stroke medical ontology, which supports AI-based stroke prediction methods using bio-signal data, to overcome these limitations. The proposed ontology approaches stroke medical knowledge from a knowledge engineering perspective. Stroke medical ontology uses OWL, the standard ontology language, for modeling. Our stroke medical ontology includes schema-level ontologies with concepts and attributes for the brain's anatomical structures, lesions, and diseases involved in a stroke. It also includes a medical term ontology covering the standard medical terminology ICD [8], SNOMED-CT [1], and FMA[2]. The above schema ontology and instance ontology are meaningfully mapped to each other by applying layered ontology modeling techniques that separate schemas from instances. Through SWRL-based inference, we infer predicted lesions, diseases, and anatomical brain structural ripple effects based on the patient's current lesions and diseases. The inferred knowledge information is provided via SPARQL[3], a standard ontology query language.

The proposed stroke medical ontology plays a role in providing medical information about strokes from the risk prediction results of machine learning and deep learning systems for stroke prediction based on bio-signals and AI. To achieve this, we developed an ontology-based stroke prediction system. We achieved 67.82% knowledge augmentation performance when comparing patients' current lesions and diseases with previously inferred lesions, diseases, and areas of disability predicted by the SWRL-based inference using emergency room data from 37 actual stroke patients.

The proposed medical knowledge ontology conservatively provides medical knowledge regarding strokes based on the small precursor lesions of strokes. Its purpose of intuitively informing the user so they can quickly receive the appropriate treatment at a hospital. In this way, we anticipate that our system will be used to prevent strokes by giving patients advanced warning.

This paper is organized as follows. Section 2 discusses the need for this study and references existing medical ontologies and stroke ontologies. Section 3 introduces the structure of the stroke medical ontology proposed in this paper. Section 4 describes the usage of the stroke medical ontology and analyzes its knowledge augmentation rate and, finally, Section 5 concludes the paper and discusses future research tasks.

II. Related Works

An ontology is a knowledge engineering method of creating a model in which computers can understand a domain's concepts and properties, as well as understanding the relationships among those concepts [9]. To develop a stroke medical ontology, what each medical concept is and how each concept is explained should be defined. This section discusses the medical knowledge ontology that comes from traditional medical knowledge.

Medical ontologies can be primarily divided into three groups [10]. The first group includes the ontologies that use standard medical terminology for medical terminology consistency. The second group includes the actor profile ontologies for discerning medical organizations or positions and responsibilities in the medical field [10]. The third group includes the ontologies that define terminology and process to manage medical workflow in a clinical decision-making system [10].

The medical ontologies in the first group include ICD, SNOMED-CT, FMA, and ICNP (The International Classification for Nursing Practice) [10]. ICD provides standard medical terminologies for diseases and symptoms affecting health conditions based on disorders [8][11]. SNOMED-CT is a set of medical terminologies that provides the codes used in clinical documents and reports, it also provides synonyms and definitions of terminology. It is considered the most comprehensive international health care terminology system [8][12]. The FMA ontology includes relationships between organisms related to anatomical structures that the human body is composed of [13]. Finally, the ICNP ontology includes nursing terminologies and nursing definitions used when diagnosing patients and plays a critical role in defining clinical priorities by systematizing medical nursing services [15].

The actor profile ontologies in the second group specify the organization and work processes used in medical field services. The K4 Care Platform, a health care service platform supporting home-care for older adults, developed the K4Care HC Model ontology to specify the performance of patients and doctors, as well as medical services processes [15]. Also, patient trajectory ontology was developed to continuously monitor patients after disease outbreaks, this system is used for correlation analysis with medical staff (patient, prescription, symptom, treatment, patient schedule) [16].

Lastly, the clinical workflow ontologies in the third group define standardized treatment processes for diseases based on

[1] https://bioportal.bioontology.org
[2] http://si.washington.edu/projects/fma
[3] https://www.w3.org/TR/sparql11-query/

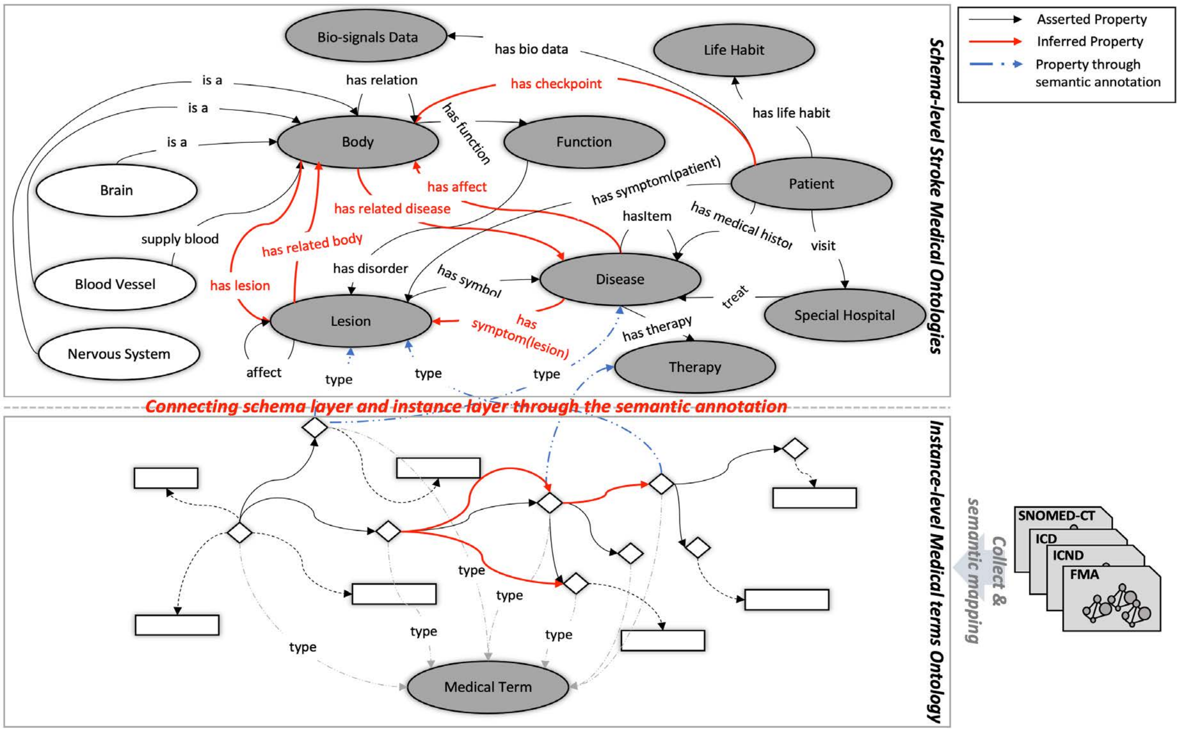

Fig. 1. Overview of the Stroke Medical Ontology

medical knowledge that should be considered in a patient's treatment process. Based on SNOMED-CT and HL7[4] (Health Level 7), an ontology has been developed to standardize clinical pathways and facilitate easier connections with EMR (Electrical Medical Records) in hospitals [17]. The Clinical Reasoning Ontology (CRO), which is based on medical papers, defines 126 medical knowledge concepts, 38 embedded reasoning concepts, and 240 unique properties used in clinical decision-making systems [18].

Thus, in the previous work mentioned above, ontology have been created for anatomical structures, symptoms, diseases, clinical processes, and concepts corresponding to treatment. They have been used in the clinical field. Stroke ontologies have also been used to support statistical analysis, analytical methods of machine learning, and deep learning to generate optimized post-care plans for stroke patients. The above ontologies have only been used by professional medical personnel as a decision-making tool for stroke analysis. However, few ontologies allowed stroke patients to judge their symptoms and provide suggestions for rapid first aid. It can be said that there is great need for a non-expert-level stroke medical ontology that will allow stroke patients themselves to make decisions in case of emergencies.

III. Development of The Stroke Medical Ontology

This section describes the detailed structure (concepts, properties, and SWRL rules) of our stroke medical ontology that supports stroke prediction systems.

In the medical fields professional standard terms should be used due to the nature of the work that takes place. To this end, the proposed ontology collects standard medical terms, such as those in ICD [8], SNOMED-CT [8], and FMA, to build an instance-level medical terms ontology. The constructed medical terms ontology performs semantic mapping with the schema-level stroke medical ontologies (body, function, lesion, disease, patient, special hospital, therapy, life habit) for stroke definition through semantic annotation (Fig. 1). By separating the schema layer from the instance layer, there is an advantage that the ontology can be developed implicitly when creating the SWRL-based rules and the SPARQL queries.

We used TopBraid Composer-Maestro Edition[5] as our ontology editor and knowledge management system that supports OWL[6] (Web Ontology Language). OWL has a richer vocabulary than RDF[7] (Resource Description Framework) and RDFS[8] (RDF Schema Language). We defined 75 concepts (TABLE I) that classify strokes into several groups and 49 properties (TABLE II) for explaining the concepts.

[4] https://www.hl7.org/fhir
[5] https://www.topquadrant.com/products/topbraid-composer
[6] https://www.w3.org/OWL
[7] https://www.w3.org/RDF
[8] https://www.w3.org/2001/sw/wiki/RDFS

TABLE I. CONCEPTS OF THE STROKE MEDICAL ONTOLOGY

Top-level Concept	***Sub Concepts***	***Axiom***	***Definitions***
Body(6[a])	Brain, Heart, Muscle, Bone, BloodVessel, NervousSystem	Body ⊑ owl:Thing[b]	The concept of defining the human body related to the stroke.
Brain(10[a])	Cerebrum, Cerebellum, BrainStem, Diencephalon, CerebralCortex, LimbicSystem, BasalGanglia, Pons, Mesencephalon, MedullaOblongata	Brain ⊑ Body	The concept of defining the brain structure.
CerebralCortex(10[a])	AnatomicalArea, FunctionalArea, BrodmannArea, Gyrus, Sulcus, Cortex, Lobe, Lobule, Regio, Segment	CerebralCortex ⊑ Brain	The concept of defining the cerebral cortex of the cerebrum.
BloodVessel(10[a])	Artery, Vein, Cpillary, CarotidArtery, CerebralArtery, CorotidVein, CerebralVein, CorticalArtery, MedullarArtery, PerforatingArtery	BloodVessel ⊑ Body	The concept of defining the blood vessel structure.
NervousSystem(17[a])	BodyStructure, Cell, Tissue, Organ, RespiratorySystem, CirculatorySystem, CentralNerveSystem, PeripheralNerveSystem, Spinalcord, SomaticNervousSystem, AutonomicNervousSyste, Stria, Tract, CraniaNerve, SpinalNerve, ParasympatheticNerve, SympatheticNerve	NervousSystem ⊑ Body	The concept of defining the nervous system structure.
Lesion(10[a])	MotorDisorder, SensoryDisorder, PerceptionDisOrder, CognitiveDisorder, PersonalityAndEmotionalChange, LanguageDisorder, TactilePerceptionDisorders, BodySchemeDisorders, Apraxia, Apraxia	Lesion ⊑ owl:Thing[b]	The concept of defining the lesion related to a stroke.
Disease(2[a])	DiseaseOftheCirculatorySystem, CerebrovascularDisease	Disease ⊑ owl:Thing[b]	The concept of defining the disease related to a stroke based on the ICD-11.
Etc. Function, Patient, SpecialHospital, Therapy, MedicalTerm, Bio-Signals-Data, LifeHabit,			
			Total Concepts: 75

a. Number of sub-concepts

b. Top-level concept defined in OWL

TABLE II. OBJECT PROPERTIES OF THE STROKE MEDICAL ONTOLOGY

Top-level Property	***Sub Properties***	***Domain***	***Range***	***Definitions***
hasFunction(2[c])	hasGeneralFunction, hasDetailedFunction	Function	Function	The property that defines connections between functions of the body.
hasRelation(17[c])	belongTo[owl:inverseOf contain,*], bounedBy[-], partOf[*], locatedIn[*], contain[*], hasFunctionalArea[owl:inverseOf haAnatomicalPosition], hasBrodmannArea[owl:inverseOf haAnatomicalPosition], hasAnatomicalPosition, divideInto[*], hasSegment, separateFrom, supplyBloodTo, flowTo, influence[*], composedTo[*], form[*], beIn[*]	Body	Body	The property that defines connections between parts of the body.
hasItem(3[c])	hasItemInDetail[owl:inverseOf hasItemInGeneral] hasItemInGeneral[owl:inverseOf hasItemInDetail], hasSequelae	Disease	Disease	The property that defines the existence of a disease.
hasAffect[owl:inverseOf hasRelatedDisease] (6[c])	block, rupture, blockByEmbolism, blockByThrombosis, blockByOcclusionOrstenosis, caseInflammation,	Disease	Body	The property that defines connections between diseases and the body.
hasCheckPoint(2[c])	hasCheckPointDirectly, hasCheckPointInDirectly	Patient	body	The property that defines connections between the patient and the body.
Etc. affect, hasSymbol, hasDisease, hasDisorder, hasLesion[owl:inverseOf hasRelatedBody], lesion:hasSymptom[owl:inverseOf hasSymbol], patient:hasSymptom, visit, hasLifeHabit, hasBioData, treat, hasTherapy, hasRelatedDisease[owl:inverseOf hasAffect], hasRelatedBody[owl:inverseOf hasLesion]				
				Total Properties: 49

c. Number of sub-properties

*. owl:TransitiveProperty

-. owl:SymmetricProperty

A. Concepts Definition

The stroke medical ontology includes top-level concepts of the human body, lesions, diseases, and treatment methods associated with stroke. It also includes patients' bio-signal data, information on their lifestyle, and on specialized hospitals the patients visited. Each concept extends to more complex concepts through the is-a relationship.

For example, the body concepts that define anatomical knowledge about the body in relation to what causes strokes is subdivided into the brain, blood vessels, and nervous systems. The brain is further subdivided into the cerebrum, cerebellum, diencephalon, and brain stem. Furthermore, the cerebrum is subdivided into the cerebral cortex, limbic system, and basal ganglia (TABLE I). The implicit super-concept extends to explicit sub-concepts that are subdivided according to the concept taxonomy.

B. Relations between Concepts

This section describes the relationships between the concepts that were described in the previous section.

The stroke medical ontology defines properties to describe concepts for defining strokes from a medical perspective. The "hasRelation" property is an upper property that defines the relationship between one part of the body and another part of the body. It defines sub-properties that define the relationships between detailed sub-concepts that follow the body concept taxonomy. For example, the brain, a sub-concept of the body, defines "contain" and "belongTo" properties, which refer to inclusion relationships about parts of the brain, to define the brain's anatomical structures. Also, cerebral blood vessels, a sub-concept of the body, define the "supplyBloodTo" property to define the brain's relationship with what supplies it blood (TABLE II).

Properties defined in the stroke medical ontology define the OWL properties' characteristics such as owl:SymmetricProperty , owl:TransitiveProperty, and owl:inverseOf. For example, the "divideInto" property, a sub-property of the "hasRelation" property and the property that defines the branch relationship of the cerebral blood vessels, is a transitive property (owl:TransitiveProperty) (TABLE II). For example, in the cerebral blood vessels' anatomical structure, the internal carotid artery branches off to form the middle cerebral artery (“internal-carotid-artery divideInto middle-cerebral-artery”). Also, the middle cerebral artery branches off to form the artery of the central sulcus (“middle-cerebral-artery divideInto artery of the central sulcus”). It is then inferred that the internal carotid artery branches into the artery of the central sulcus (“internal-carotid- artery divideInto artery of the central sulcus”).

C. SWRL

SWRL is an ontology-based language to describe rules [19]. We developed nine SWRL rules to derive the parts of the brain that may suffer from disability and to predict lesions and diseases in stroke patients (TABLE III). The above SWRL rules behave recursively.

TABLE III. SWRL RULES OF THE STROKE MEDICAL ONTOLOGY

SWRL rules	
function:hasDisorder(?x, ?y) ˄ lesion:affect(?y, ?z) → function:hasDisorder(?x, ?z)	(1)
body:hasFunction(?x, ?y) ˄ function:hasDisorder (?y, ?z) → body:hasLesion(?x, ?z)	(2)
body:hasLesion (?x, ?y) ˄ lesion:hasSymbol (?y, ?z) → body:hasRelatedDisease(?x, ?z)	(3)
lesion:affect (?x, ?y) ˄lesion:hasSymbol (?y, ?z) → lesion:hasSymbol (?x, ?z)	(4)
lesion:hasSymbol(?x, ?y) ˄ disease:hasItemInDetail (?y, ?z) → lesion:hasSymbol (?x, ?z)	(5)
patient:hasSymptom(?x, ?y) ˄ lesion:hasRelatedBody(?y, ?z) ˄ bloodvessel:supplyBloodTo (?b, ?z) → patient:hasCheckPointDirectly (?x, ?b)	(6)
patient:hasCheckPointDirectly (?x, ?y) ˄ bloodvessel:dividedInto (?y, ?z) → patient:hasCheckPointRelated (?x, ?z)	(7)
patient:hasSymptom(?x, ?y) ˄ lesion:affect(?y, ?z) → patient:hasSymptom (?x, ?z)	(8)
patient:hasSymptom(?x, ?y) ˄ lesion:hasSymbol(?y, ?z) → patient:hasMedicalHistory (?x, ?z)	(9)

IV. EXPERIMENT AND SYSTEM IMPLEMENTATION

We experimented with the knowledge augmentation rates of lesions and diseases through a SWRL-based inference to verify our stroke medical ontology. We selected five out of 37 elderly patients with an actual stroke prediction of 80% or more, according to an older stroke prediction system from a previous study that used EMG sensors [7], and used their emergency room data as the dataset for this experiment. Predictions for which body parts were expected to have a disability as well as lesion and disease predictions for the five patients were carried out using the queries.

TABLE IV. RESULT OF AN EXPERIMENT

Categories	***Patients***				
	P1	***P2***	***P3***	***P4***	***P5***
Current’s Lesions(1)	2	4	3	5	3
Current’s Diseases(2)	3	3	2	2	3
Inferred Lesions(3)	5	3	4	6	3
Inferred Diseases(4)	3	2	6	3	2
Inferred Body Portions(5)	6	3	7	5	8
Asserted Knowledge(6) (6) = (1) + (2)	5	7	5	7	6
Inferred Knowledge(7) (7) = (3) + (4) + (5)	14	8	17	14	13
Knowledge Augmentation Rate(%)(8) (8)=((7)/((6) + (7)))*100	73.7	53	77.3	66.7	68.4
Average Knowledge Augmentation Rate: 67.82%					

Fig. 2. The user UI of our Ontology-based Stroke Prediction System.

Table 4 above shows the knowledge augmentation's success rate for predicting the body parts (brain, cerebrovascular, nervous system), the lesions, and the diseases, these predictions were inferred from ontology-based reasoning and the results were compared to the patients' current lesion and disease status. As shown in the above results, the stroke medical ontology was able to provide comprehensive information based on relevant medical knowledge in contrast to existing stroke prediction systems that just produce a value. Our system is able to use patient symptoms to predict current disease information. We think our system offers an effective way to prevent strokes. information. We think this is an effective way to prevent stroke.

We developed the ontology-based stroke prediction system based on results inferred from a stroke medical ontology to increase the user's perception of how useful the information provided is. Figure 2 shows the user UI of the ontology-based stroke prediction system.

V. Conclusion

We presented a stroke medical ontology developed to medically reinforce the results of EMG bio-signal-based machine learning and deep learning-based stroke prediction systems that we described in previous studies. The proposed ontology was able to infer in which brain region a patient has a disability as well as predict lesions and diseases based on the stroke prediction results. Also, we developed the ontology-based stroke prediction system to provide medical information related to these strokes graphically. We demonstrated a medical knowledge augmentation rate of 67.82% by applying SWRL-based inference.

COVID-19 has made it difficult to perform experiments that focus on the elderly and collect their bio-signal data. Therefore, in our future research we plan to promote consultation and practicality with hospital medical staff to improve and verify our system's prediction accuracy as well as verify its availability. Besides, we plan to develop systems that are not limited to cerebrovascular diseases but can tackle other diseases and provide predictive results on these through more accurate and in-depth interpretation of actual biological signals from elderly patients combined with medical knowledge.

Acknowledgment

This work was supported by the National Research Council of Science & Technology (NST) grant by the Korea government (MSIP) (No. CRC-15-05-ETRI).

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