Modeling a Smart Teleradiology: Decision Support System based on Ontology

EUSTACHE MUTEBA A.[1], PATRICK ANELIA L.[2]
[1]Correspondent of International Medical Informatics Association,
P.O. Box 14769, Kinshasa,
DR CONGO

[2]Interdisciplinary Center for Research in Medical Imaging,
Department of Radiology, University Clinics of Kinshasa,
DR CONGO

Abstract: - Increasingly, hospitals are producing information related to additional examinations for reasons of in-depth investigations or diagnoses. Medical imaging plays an essential role in medical action, mainly for diagnosis, therapeutic planning, intraoperative navigation, postoperative monitoring, and biomedical research. From the perspective of Universal Health Coverage, teleradiology is one of the solutions to the lack of radiologist practitioners in certain territories. Given the situation of the health system in developing countries and in particular in DR Congo, we therefore aim to contribute by providing a solution under a project related to teleradiology. The system designed to make a link between clinical information, data extracted from images, and the radiological ontology for decision-making based on semi-supervised machine learning. This article presents the theoretical foundations of the study and highlights the implementation of our radiology ontology called Smart Ontology of Radiology (SORad).

Key-Words: - Teleradiology, Image analysis, Ontology, Semi-supervised machine learning, Intelligent system, Decision support.

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1 Introduction

Increasingly, hospitals are producing information related to additional examinations for reasons of in-depth investigations or diagnoses.

Medical images are an integral part of healthcare data that are acquired mainly for diagnosis, therapy planning, intraoperative navigation, post-operative monitoring, and biomedical research, [1].

It should be noted that the global teleradiology market size was valued at USD 2.44 billion in 2022 and is anticipated to grow at a compound annual growth rate (CAGR) of 12.9% from 2023 to 2030. The growth is majorly driven by the increasing prevalence of target diseases, and rising demand for teleradiology for second opinions and emergencies, [2].

As stated in [3], the ability to exploit data, in particular imaging, is at the heart of the challenges of tomorrow's medicine.

However, given the situation of the health system in developing countries and in particular in DR Congo, we noted that there are the following recurring priority problems: (a) low coverage (b) weak operational capacity of structures at all levels to carry out interventions, (c) poor quality of care and services offered, (d) low use of available care and services, and (e) weak public accountability of health services.

From the perspective of Universal Health Coverage, teleradiology is one of the solutions to the lack of radiologist practitioners in certain territories.

We therefore aim to contribute by providing a solution under a project related to teleradiology. The project involves the radiology department of the University Clinics of Kinshasa (CUK). The choice of the CUK is justified by its position on the national level as a major center for medical research application given the number of experts.

Our system is called Smart Teleradiology. The system designed to make a link between clinical information, data extracted from images, and the radiological ontology for decision-making based on semi-supervised machine learning.

To enable optimum and specialized patient care through timely interventions by expert radiologists in any location at any time of day, our system is built in a cloud.

This article presents the theoretical foundations of the study and highlights the implementation of our radiology ontology called Smart Ontology of Radiology (SORad).

2 Methods

The methodology adopted to develop our system involves classical analysis of the different concepts involved. This is a classic way that gives the limits of our study.

2.1 Radiology Information System (RIS)

A Hospital Information System (HIS) is a federation of functionally distinct but not disjointed subsystems, within and between which flows of information circulate. The radiology information system is one of the subsystems.

As clearly stated in [4], radiological center within the hospital information system (HIS) requires a special and its information system, radiology information system (RIS).

Ultimately, a radiology information system is a subsystem that manages medical imagery and associated data.

2.1.1 Different Functionalities of RIS

The RIS is an element of the HIS that is dedicated to interacting with the medical record.

Within RIS there is the PACS (picture archiving and communication systems) as an important component.

PACS is a computerized means of replacing the roles of the conventional radiological film: images are acquired, stored, transmitted, and displayed digitally, [5].

In general, the RIS provides the following functions: radiology examination order form, modality interface and image acquisition, processing and restitution of images, digital reporting and result transmission, integration with the HIS medical record, archiving in PACS, and Images tracking.

2.1.2 Nature and Type of Radiology Data

Routine clinical visits of a single patient might produce digital data in multiple modalities, including image data (i.e. pathology images, radiology images, and camera images) and non-image data (i.e. lab test results and clinical data). The heterogeneous data would provide different views of the same patient to better support various clinical decisions (e.g. disease diagnosis and prognosis, [6].

2.2 Imaging Modalities

It should be noted that in radiology, a medical image is a materialization in the form of images of anatomical or functional information in vivo of parts (organs, tissues, cells) of the human body, as well as the data extracted or derived from these images.

To obtain image data, there are both hardware and software processing operations.

On the hardware side: it is the image acquisition process by an image constructor device. An image is the optical representation of an object illuminated by a radiation source. The following elements are present in an image formation process: an object, a radiation source (visible light, X-rays, electrons, etc.), and an image formation system, [7].

On the software side: it is the image processing. Image processing may include the following steps: Image import via image acquisition tools, image manipulation, and analysis.

Table 1. Types and Mechanisms of Different Imaging Modalities

Modalities	Mechanisms	Types	2D/3D
X-ray	X-ray absorption	Morphological	2D
Digital angiography	X-ray absorption	Morphological	2D
Rotational angiography	X-ray absorption	Morphological	3D
CT (scanner)	X-ray absorption	Morphological	3D
Ultrasound	Ultrasound reflection	Morphological	2D sections
Ultrasound 3D	Ultrasound reflection	Morphological	3D
Scintigraphy	Emission of gamma photons	Functional	2D projection
Tomoscintigraphy	Emission of gamma photons	Functional	3D
PET	Émission de positons	Functional	3D
MRI	Echoes of the magnetization of the nuclei	Mixed	3D

Imaging modalities relate to image acquisition techniques using imaging equipment. As stated in [8], imaging modalities are often categorized by the method in which images are generated normally by physical phenomena. Usually, the physical phenomena, on which all the stages of image production can be: X-rays (Radiology), gamma rays (Nuclear Medicine), magnetic waves (Magnetic Resonance Imaging), ultrasonic waves (ultrasound), and optics (endoscopy).

Modern radiological imaging uses a standard called Digital Imaging and Communications in Medicine (DICOM), [9]. The DICOM incorporates standards for imaging modalities as described in Table 1.

2.3 Ontology

Defining an ontology for knowledge representation means defining, for a given domain and problem, the functional and relational signature of a formal language of representation and the associated semantics, [10].

A formal system represents a specific domain of knowledge using basic elements, the concepts, that are defined and organized each one in relation to the others, [11].

In practice, the modeling of knowledge by an ontology will have to take the following elements: semantics (knowing how to understand each other), syntactics (knowing how to communicate), and technique (being able to communicate).

Assuming that the physician has a cognitive causal model for performing a medical act (investigating, diagnosing, and prescribing) of a patient. This causal model, incorporating the expert's knowledge of anatomy and physiology, can be used to simulate the normal working of the body, its pathological behavior in a diseased state, and the idiosyncrasies that characterize a particular patient.

Therefore, we can imagine that this causal model influences the creation of the classes
of a medical ontology.

In practical terms, developing an ontology includes:
- defining classes in the ontology,
- arranging the classes in a taxonomic (subclass–superclass) hierarchy,
- defining slots and describing allowed values for these slots,
- filling in the values for slots for instances.

In radiology, there are ontologies which of course have different specificities, to date, the radiology lexicon, Radiological Society of North America's radiology lexicon (Radlex) ontology [12], [13], seems the most widespread.

In any case, the integrated Radiology Gamuts Ontology (RGO) system is interesting. The RGO is an ontology that links diseases and imaging findings to support differential diagnosis in radiology, to terms in three key vocabularies for clinical radiology: the International Classification of Diseases, version 10, Clinical Modification (ICD-10-CM), the Radiological Society of North America's radiology lexicon (RadLex), and the Systematized Nomenclature of Medicine Clinical Terms (SNOMED CT), [14].

2.4 Radiology Decision Support

In medical practice, the clinical decision support systems (CDSSs) rely on formalized knowledge bases and are usually integrated into electronic patient records to assist the clinician in her everyday practice, [15].

The radiology decision support takes its source in the modalities of the images according to the specific problem of the patient as presented in the medical record

Among the most concerned activities in radiology is the interpretation of images for diagnosis.

Technically, the interpretation of medical images requires the modeling of spatial relationships and the view of the appearances of objects. The modeling of spatial relationships uses segmentation and recognition.

The use of computer-assisted decision support is not new in radiology. As mentioned in [16], radiology requires diagnosis and decision-making under uncertainty and AI may help automate some of the labour-intensive tasks such as radiograph interpretation and reporting.

It is stated that machine learning, the cornerstone of today's artificial intelligence (AI) revolution, brings new promises to clinical practice with medical images, [17]. In accordance with [18], initially, machine learning typically begins with the machine learning algorithm system computing the image features that are believed to be of importance in making the prediction or diagnosis of interest.

Moreover, it is interesting to know that recent advances in machine learning have the potential to recognize and classify complex patterns from different radiological imaging modalities such as x-rays, computed tomography, magnetic resonance imaging, and positron emission tomography imaging, [19].

In the previous section, it was discussed and demonstrated that ontology can play an important role in decision support regarding the protocol of imaging findings.

2.5 Teleradiology

Teleradiology is the remote practice of radiological medicine. It is one of the telemedicine applications that benefit from the longest clinical experience and the greatest technological maturity. Teleradiology mainly includes telediagnosis and teleexpertise.

Telediagnosis consists, for the radiologist, of organizing remotely and under his control the performance, by a manipulator, of an imaging examination then interpreting it and reporting its result, in the most similar way possible to what would have been done in an office or an establishment.

Teleexpertise consists of allowing a healthcare professional to remotely seek the opinion of one or more healthcare professionals because of their training or their particular skills for the care of a patient.

Teleradiology can help increase imaging efficiency and mitigate both geographic and temporal discrepancies in imaging care, [20].

3 Results

Let us take advantage of the different techniques previously described to develop a smart teleradiology system. It is a very complex system as you can see in its architecture. However, we will present to you the essentials, namely the models of our: machine learning, ontology, and decision support. For the sake of pragmatism, we carry out simulations.

3.1 Smart Teleradiology System Architecture

The system architecture, as presented in Figure 1, is structured around the following components: User Interface, PACS, Semi-supervised Machine Learning, Ontology, and Decision Support.

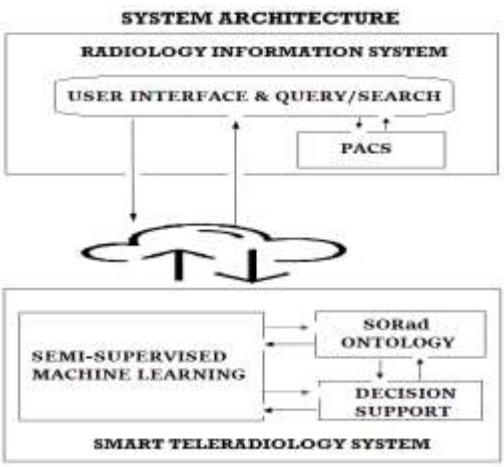

Fig. 1: Diagram of the Smart Teleradiology System

3.2 Semi-Supervised Machine Learning

The idea behind Semi-Supervised Machine Learning, [21], stands somewhere between supervised learning (in which all training examples are labeled) and unsupervised learning (in which no label data are given).

The SSML-based problem-solving approach caught our attention for its realistic aspect. In our previous work [22], we implemented and experimented with this method to perform the automatic diagnosis of malaria. However, this was limited to microscopic images. And so for this current study which relates to macroscopic images, we have made modifications especially in terms of the image analysis algorithms.

A succinct description of the framework of SSML is shown in Figure 2 and described below:

- HumanExpert.class: allows the user interface.
- Manager.class: provides activities of managing and controlling all components of SSML.
- Contractor.class: supports and allows grants to the manager.class to perform activities. This ensures and meets SSML requirements in terms of flexibility and efficiency under a contract specification, [23].
- PACS.class: provides activities to manage file acquisition.
- Uploader.class: provides activities to manage uploads or acquisition of files.
- Viewer.class: provides activities to display files.
- ImageAnalyzer.class: allows the extraction of significant information and manages image analysis.
- Extractor.class: quantifies the significant characteristics of objects in the image and selects regions of interest containing relevant information.
- PatternBuilder.class: provides activities to build pattern from a selected image region. It is the pre-classification process.
- Classifier.class: provides label assignment and classification activities based on a prediction model.
- Profiler.class: provides clustering activities based on Classifier results.

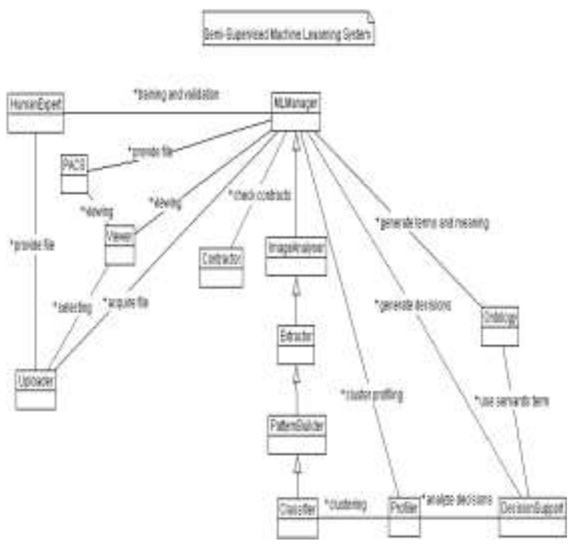

Fig. 2: Framework of Semi-Supervised Machine Learning (SSML)

3.3 Smart Ontology of Radiology

The developed ontology is called “Smart Ontology of Radiology (SORad)”. SORad is based on a multiaxial classification and it is built based on aspects related to topography, morphology, etiology, functional, treatment, and procedure.

We present in the following six figures, namely Figure 3, Figure 4, Figure 5, Figure 6, Figure 7 and Figure 8, that show different views of our first version of SORad, It is structured around 5 main concepts: Diagnosis, Equipment, Human, Imaging, and Procedure classes.

Fig. 3: SORad abstract classes

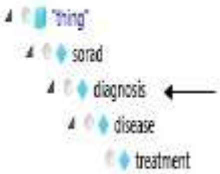

Fig. 4: Diagnosis abstract class

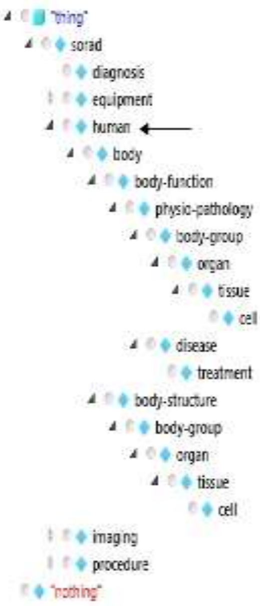

Fig. 5: Human class

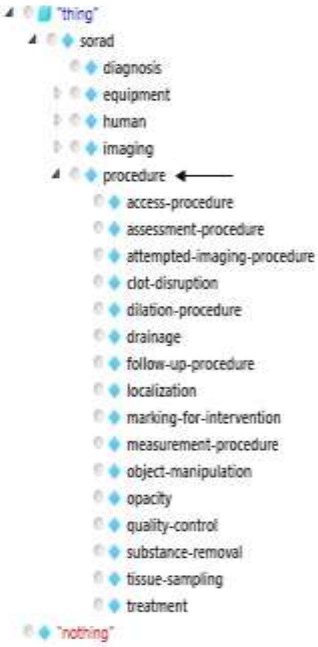

Fig. 6: Procedure class

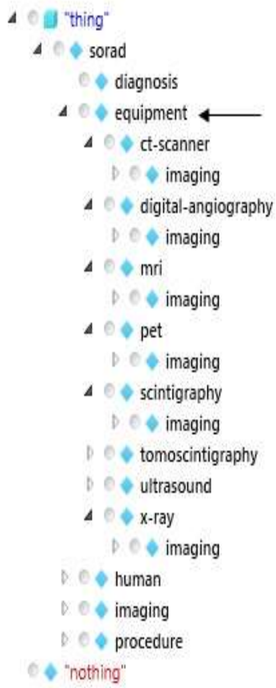

Fig. 7: Equipment class

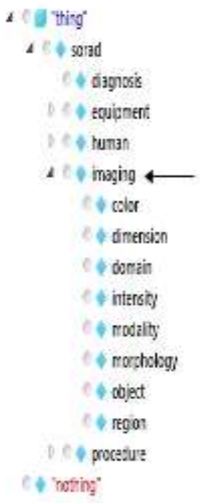

Fig. 8: Imaging class

3.4 Smart Decision Support

When we interpret the SSML, there is a straight line in the center that goes from the ImageAnalyzer class to the Classifier class. The Profiler class is the bridge between the Single Block and the Decision Support class. Indeed, once the machine provides a classification, the DecisionSupport class will have to select the results obtained based on the calculated and/or predefined rule-criteria.

Ultimately, radiology relies on exchanges between medical personnel and uses language as a vector of communication through requests, protocols, and reports. Considering that medical imaging is by definition linked to the image and that this is in its production as well as in its interpretation. The radiologist interprets and makes the image speak using words. There is a clear need for knowledge management to facilitate common understanding among radiologists.

The SORad ontology can act in carrying out the protocol to give meaning and support the diagnosis. At this level, a special component of Natural Language Processing (NLP) intervenes. This is the Automatic Radiology Protocol Generator (ARPG).

3.5 Simulation

The simulation focuses on the initial results of the SORad ontology component. The screenshots in Figure 9, Figure 10 and Figure 11, show the user interface and query/search terms in SORad.

4 Discussion and Conclusion

Presenting a model and methodologies to develop a smart teleradiology system is the aim of this article.

Fig. 9: Screenshot of the term related to human class

Fig. 10: Screenshot of the term related to equipment's class

Fig. 11: Screenshot of the term related to image's class

The architecture of the system shows that there are four integrated components, namely: Radiology Information System, Semi-supervised Machine Learning, Ontology and Decision Support. Each of them plays a role.

In itself, the smart teleradiology system is an essential solution for access to health care and to enable optimum and specialized patient care through timely interventions by expert radiologists in any location at any time of day, particularly, in developing countries.

Upstream, the radiology information system intervenes as an interface with the cloud. It manages the patient's clinical information, acquisition, transmission, and traceability of images.

The core of the system is semi-supervised machine learning. This choice is explained by the fact that an SSML is controllable, especially given the delicacy of radiological imaging.

It turns out that a decision support system supported by an SSML interacting with a dedicated ontology allows causal reasoning which gives the ability to explain complex logical interconnections between investigation, diagnosis, and prescription about a given case.

Furthermore, for pragmatic reasons, a simulation is performed and presents the SORad ontology.

This initial implementation was carried out on our Virtual Community of Healthcare Facilities development platform, [24]. Note that the project is underway for a prototype. And as we go along, we bring innovations. It's like leveraging Radiology Gamuts Ontology (RGO) to enrich our system.

Certain aspects of our study will be the subject of other future articles.

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Contribution of Individual Authors to the Creation of a Scientific Article

- Patrick Anelia posed the problem and provided useful specifications relating to the field of study: "radiological imaging".
- Eustache Muteba carried out all theoretical and technical aspects, and also wrote the paper.

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Conflict of Interest

The authors have no conflicts of interest to declare.