Semantic Description of Liver CT Images: An Ontological Approach

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***Abstract*—Radiologists inspect CT scans and record their observations in reports to communicate with physicians. These reports may suffer from ambiguous language and inconsistencies resulting from subjective reporting styles, which present challenges in interpretation. Standardization efforts, such as the lexicon RadLex for radiology terms, aim to address this issue by developing standard vocabularies. While such vocabularies handle consistent annotation, they fall short in sufficiently processing reports for intelligent applications. To support such applications, the semantics of the concepts as well as their relationships must be modeled, for which, ontologies are effective. They enable software to make inferences beyond what is present in the reports. This work presents the open source ontology ONLIRA (Ontology of the Liver for Radiology), which is developed to support such intelligent applications, such as identifying and ranking similar liver patient cases. ONLIRA is introduced in terms of its concepts, properties, and relations. Examples of real liver patient cases are provided for illustration purposes. The ontology is evaluated in terms of its ability to express real liver patient cases and address semantic queries.**

***Index Terms*—Ontology, Liver, Radiology**

I. Introduction

Radiologists document imaging observations for communicating with medical professionals. A radiology report is a medico-legal document that serves as a communication link between a radiologist and a referring physician. It consists of the observations of a radiologist regarding scanned images of a patient. Clinicians, radiologists, and peers are interested in the reports to retrieve information for assistance in diagnosis, education, comparison, and improving standards [1]. The utility of radiology reports may extend beyond physician interpretation to support these needs by, for example, automatically identifying similar cases, ranking, and summarization.

Radiology reports are prepared according to institutional conventions and facilities. Personal preferences of a radiologist may also influence the report, such as a tendency to report detailed versus brief listing of observations [2], [1]. In such cases, it is not clear whether the omission of an observation in a report implies that no such condition was observed or that it was not considered important by the radiologist to report. In practice it is common for radiology reports to be unstructured and mostly verbose [3]. Ambiguous phrases are common in such documents, which may lead to misinterpretation. Natural language documents are difficult to process and their effectiveness is limited (see Section IV). Furthermore, interoperability issues that arise with different institutions and countries, as in the case of teleradiology [3], make the problem even more challenging.

For effective and long term use of radiology reports, it is beneficial to maintain structured and standardized reports [4]. International standards for vocabularies have been developed to facilitate consistency, reduce subjectivity, and automate processing. One formal ontology is the Foundational Model of Anatomy (FMA) [5] for anatomical information and some of the well known vocabularies are SNOMED CT [6] for clinical information and the International Classification of Diseases version 10 (ICD-10)[1] for disease information. RadLex [7] is an extensive lexicon for radiology that supplements FMA and SNOMED CT. It is increasingly used by a variety of health related organizations for reporting and decision support systems, research, and eduction. RadLex addresses standardization issues very well, however, it is limited in the support it can offer for intelligent processing since it lacks semantic relations. Semantic relations themselves are processable and thus useful in supporting intelligent applications such as semantic searching and browsing, case similarity, classification, and automated reporting (see Section IV for

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[1] http://apps.who.int/classifications/icd10/browse/2010/en

further discussion). This is due to capturing the relation as well as the related objects leading to more complex processing and reasoning.

This paper presents ONLIRA[2](Ontology of Liver for Radiology), which was developed as part of the CaReRa project[3] with the aim of supporting intelligent software tools for liver patients. ONLIRA specifies the semantics of liver imaging observations. Our evaluation of ONLIRA revealed that it is sufficiently expressive to capture most statements present in radiology reports. Reports created with ONLIRA may be semantically searched and yield higher precision and recall values in comparison to keyword searching of textual reports. The remainder of the paper is organized as follows: Section II presents ONLIRA, Section III evaluates ONLIRA in terms of expressiveness and retrieval performance. Section IV discusses related work and Section V presents future work and conclusions.

II. ONLIRA

ONLIRA aims to model the *imaging observations of the liver* domain with an emphasis on properties and relations between the liver, hepatic veins and liver lesions. The design of ONLIRA was based on elicitation sessions with radiologists for gaining insight into imaging observations of the liver. Each session was structured in terms of clarifications and questions related to earlier sessions, validation of concepts via concrete examples, and detailed elicitation of new concepts. Real liver patient reports were used during these meetings to assure our evolving design was sufficiently expressive. This section describes ONLIRA through examples. Parts of the ontology as well as the examples are presented with figures to highlight significant aspects. In these figures, ovals depict concepts/instances, arrows labeled with a relation name depict relationships between concepts/instances, and boxes containing property value pairs depict properties.

Before starting modeling, RadLex was carefully examined to determine relevant concepts. Communications with the RadLex team resolved any issues regarding concept associations. Considering the wide use of RadLex, associations with the RadLex terms were kept for interoperability purposes.

[2]ONLIRA is available online: http://vavlab.ee.boun.edu.tr/pages.php?p=research/CARERA/OnliraDownload.php

[3]CaReRa—Content Based Case Retrieval In Radiological Databases (Cases of Liver Diseases) is supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) and part of the COST Action “Semantic Keyword-based Search on Structured Data Sources (KEYSTONE)” (IC1302) http://www.vavlab.ee.boun.edu.tr/pages.php?p=research/CARERA/carera.html.

Three aspects of liver were considered during modeling. First, essential concepts, such as a lobe or a lesion, are represented. Second, individual properties of these concepts, such as the size or density of a liver, are captured. Finally, the relationships between the concepts are captured. The relations are important because they describe how different concepts relate to each other. For example, between a liver concept and a lobe concept, one can specify a *hasLobe* relation to show that a liver contains lobes. Developing ONLIRA in OWL enables us to clearly specify cardinality or functionality requirements among relations. For example, a liver can have at most one left lobe, while it can have many lesions. Or, size property can be specified both for a liver and a given lobe, but not for a segment. These constraints are critical in specifying a domain rigorously. With OWL in hand, it was possible to develop a realistic ontology of the liver. However, the domain that describes imaging observations of the liver is large. In order to narrow down our scope, we identified the following requirements based on the elicitation sessions and built our ontology accordingly:

Liver: The anatomical properties of the liver, such as its contour, size, density, its lobes should be described. Additionally, for the referential model of segments and regions must be defined as this is crucial in describing the location of an anomaly.

Lesion: The characteristics of a lesion, such as size, margin, shape, contrast pattern, composition, calcification, density, and its contents must be defined. Likewise, clusters of lesions must be defined in terms of its largest lesion.

Hepatic vascularity: The veins within a liver should be described.

Relationships: The relationships between the concepts must be defined. Relationships associate concepts via semantic relations, such as a lesion being *located* within a segment. The representation of relationships in this ontology, in contrast to lexicons, enable semantic reasoning which is a prerequisite for intelligent applications, such as semantic searching of reports.

Liver: This is the basic concept in ONLIRA that allows us to describe various properties of the liver, such as its size, density, and so on. These are represented as data properties in OWL. For example, the size of a liver is represented as the greatest craniocaudal dimension. The craniocaudal dimension is defined with the :*hasCraniocaudalDimension* property and assigned an integer value indicating millimeters. For example, the statement $Liver_1$:*hasCraniocaudalDimension* $\{210\}$ states that a liver

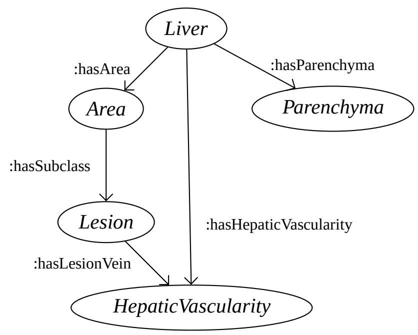

Fig. 1: The relations between *Liver*, *Area*, *Lesion*, *HepaticVascularity* and *Parenchyma*.

TABLE I: The assertions of :*isLocatedInRegion* relation for liver segments.

Segment Instance	**Region Instance**
SegmentII, *SegmentIII*	*LateralRegion*
SegmentIV	*MedialRegion*
SegmentV, *SegmentVIII*	*AnteriorRegion*
SegmentVI, *SegmentVII*	*PosteriorRegion*

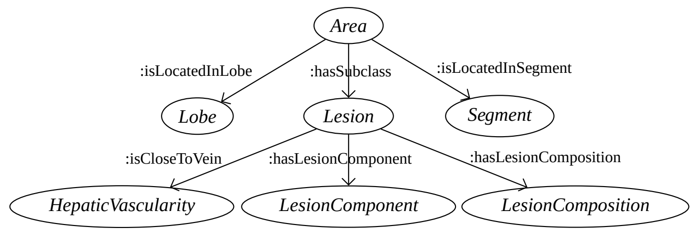

Fig. 2: The relations between *Lesion* and other concepts.

that is referred as Liver_1 has craniocaudal dimension of 210mm. In addition to defining the size of the liver, sizes of each lobe of the liver can also be defined. Another important aspect of size is its change over time. The :*hasSizeChange* property specifies a change in the liver size, such as increased. For example, a particular right lobe instance, RightLobe_1, has enlarged is stated by: $\mathit{RightLobe}_1$:*hasSizeChange* {'increased'}.

Further, a liver's relation to other concepts such as a lesion or a parenchyma can be specified using relations in OWL. Some of these are shown in Figure 1. Each liver contains *parenchyma*, a connective tissue. To represent properties of this tissue, we can identify parenchyma of a given liver, using the :*hasParenchyma* functional property. The fact that the property is functional ensures that each liver has one parenchyma. Each liver is composed of three lobes: *RightLobe*, *LeftLobe* and *CaudateLobe*. The :*hasLobe* property relates a *Liver* to each of its *Lobe*s. A liver can only have one instance of each lobe. Hence, a maximum cardinality restriction is specified for each lobe (i.e. maximum 1 *RightLobe*).

To refer to particular parts of the liver, an 8-segment referential model is used. Each *segment* instance refers to a segment in the *Liver*. The *Liver* and the *Lobe* can only be segmented by specific segments. This is specified by imposing restrictions on the :*isSegmentedBy* property. Hence, for example, caudate lobe can only be segmented by Segment 1, whereas left lobe can be segmented by Segments 2, 3, or 5. Another manner of referencing parts of the liver are by *region*s. There are four instances of *Region* named *AnteriorRegion*, *LateralRegion*, *MedialRegion* and *PosteriorRegion*. Table I shows the relationships between *Region*s and *Segment*s.

There may be abnormal *areas* of the liver a radiologist wishes to identify. The margin, size, shape, and density of an area can be specified. For example, the shape of the area is described with the :*hasAreaShape* property that may take the following values: band, fusiform, linear, nodular, ovoid, serpiginious, and other. The density of an area is represented with :*hasAreaDensity* data property that takes a value of hyperdense, hypodense, or isodense. The :*isCalcified* property indicates whether an area is calcified. If so, a second data property, :*hasCalcification*, specifies the type of calcification: coarse, focal, millimetric, punctate or scattered.

Lesion: A particularly important type of an area is a lesion. ONLIRA defines *Lesion* as a subclass of an *Area*. A lesion is characterized by additional properties to basic *Area* properties. The relations of *Lesion* are shown in Figure 2.

The location of a lesion may be described in relation to a vasculature proximity, which is considered important with respect to estimating the progression of the condition. Such proximity is described as adjacent, bended, and so on. This proximity is specified in relation to a specific vein specified with the :*isCloseToVein* property.

Additionally, properties that pertain to internal composition of the lesion can be specified. For example, the fact that a lesion contains a debris and its location with respect to the lesion (e.g., floating inside) can be specified. Similarly, an observation of leveling can be described (e.g., fluid-gas) to express the internal composition.

There are various lesion components, such as septa or polyp, that can further be described in ONLIRA. For these components, one can specify whether it is calcified (e.g., capsule or polyp). If a component is indeed calcified, a second property describes the calcification type that is observed. For some components, such as septa, the size in terms of its width and diameter can be described. For others, such as a wall, its size is merely a reflection of thickness.

A lesion's internal composition, such as cystic, solid, and so on, can also be specified. Each composition can further be classified. For example, abscess and cystic with debris are subclasses of cystic, whereas predominant solid is an example subclass of solid.

Hepatic vascularity: Characteristics of the hepatic vascular system may be out of the ordinary or a lesion may be described in relation to a specific vein. In ONLIRA, hepatic vascular system is represented with the *HepaticVascularity* concept. The liver contains three vascularity types: *HepaticArtery*, *HepaticPortalVein* and *HepaticVein*. *LeftPortalVein* and *RightPortalVein* are subclasses of *HepaticPortalVein*. *LeftHepaticVein*, *MiddleHepaticVein* and *RightHepaticVein* are subclasses of *HepaticVein*. Liver can only have one instance of each type of vein. Hence, a maximum cardinality restriction is specified for each type of vein. The vasculature of liver is basically specified in terms of the vein lumen diameter (e.g., increased) and vein lumen type (e.g., obliterated).

III. Evaluation

A. Qualitative Assessment

We have worked with 30 radiology reports of different patients to demonstrate the expressivity of ONLIRA. Here, we have identified the following sample report texts (examples) to evaluate ONLIRA to demonstrate how and to what extent we can represent these statements. For each example, we depict how the concepts are related and what properties apply with a figure.

1: "The liver's location and margin is normal. Its size has been observed to be enlarged (Craniocaudal dimension is 195mm). The density of the parenchyma shows steatosis and is significantly decreased. Portal venous system is observed to be normal." We depict the ontological construction of this example in Figure 3. Note that since ONLIRA does not contain a concept for steatosis, we do not express it.

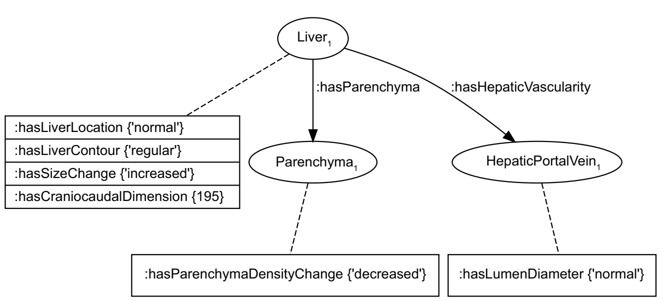

Fig. 3: Description of an enlarged liver, decreased parenchyma density and normal hepatic portal vein (Ex. 1)

2: "The liver's size, location, and margin is normal. The density of the parenchyma is homogeneous. A hypodense lesion with a diameter of 3mm and an indistinct margin has been observed in the liver's 7th Segment." This example is depicted in Figure 4.

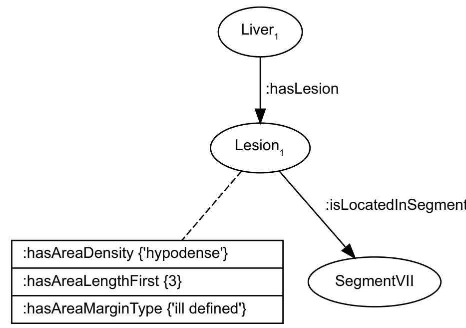

Fig. 4: Description of a liver with a hypodense lesion in Segment 7 (Ex. 2)

3: "The liver's location and margin is normal. The density of the parenchyma is decreased. In the liver parenchyma, multiple nodular, hypodense lesions with peripheric contrast pattern have been observed, such that the largest of the lesions is subcapsular localized in Segment 2 with size 2.5x3.5 cm, an indistinct margin has been observed." This example is depicted in Figure 5.

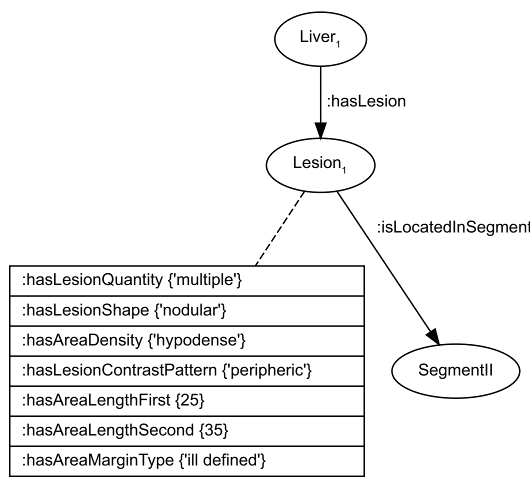

Fig. 5: Description of the largest lesion in a hypodense, nodular, lesion cluster (Ex. 3)

The examples presented in this section (extracted from real case reports) demonstrate that ONLIRA is capable of expressing most of imaging observations and covers the requirements elicited during the initial phase of this work. There are a few conditions that are not covered, such as a lesion being located *between* segments or spans over several segments. These will be addressed in the next version of the ontology.

B. Quantitative Assessment

Next, we studied how an ontology could help in searching radiology reports. Since the radiology reports were generally written in natural language, an obvious method for searching them was a keyword-based search using natural language processing (NLP). If the reports had been described ontologically as advocated in this paper, the reports could have been searched through description logic query languages such as DL query [8]. To illustrate this, we took 30 radiology reports of different patients written in natural language and converted them into ONLIRA instances. We compared two different approaches, an ontology-based (semantic search) and an NLP-based approach (keyword search) for searching radiology reports. To highlight differences between the two approaches, we described five queries expressed in both DL query and keywords. A report was retrieved if it satisfied the DL query or it contained all of the keywords in the search query.

To establish a gold standard, two board certified radiologists manually evaluated each query to decide which reports should be retrieved. Radiologists agreed with each other on 86% of the query results (kappa=0.86). We evaluated both approaches against the gold standard by comparing their precision and recall. Precision is the proportion of truly retrieved reports to the total number of reports retrieved. Recall is the proportion of truly retrieved reports to the total number of reports that should have been retrieved. Five queries with corresponding precision (p1, p2), recall (r1, r2) results are shown in Table II. p1 and r1 were computed according to the first radiologist, p2 and r2 were computed according to the second radiologist.

q1–Find all reports related to a lesion: In both approaches, 12 reports were retrieved with a precision of 1 (12/12), whereas both approaches achieved r1 of 0.80 (12/15) and r2 of 0.86 (12/14). Non-retrieved reports contained area descriptions and both radiologists considered areas as lesions. In ONLIRA, a lesion is defined to be an area but the inverse is false. Hence, some reports have not been matched. In keyword search, the word ’area’ did not match the word ’lesion’; the same reports were not retrieved there, either.

q2–Find all reports that contain a lesion in posterior region of liver: In semantic search, six reports were retrieved with a precision of 1 (6/6). ONLIRA describes segment and region relation and it can infer the region given segment number even when the region is not explicitly stated in reports. Reports were retrieved with r1 of 1 (6/6) and r2 of 0.86 (6/7). No reports were retrieved with keyword search because the word ‘posterior’ was not contained in any of the reports where location of lesions were only described with segment information.

q3–Find all reports that contain a lesion that has a size greater than 10mm: In semantic search, five reports were retrieved with a precision of 1 (5/5). As in the first query, areas were considered as lesions by both radiologists. Therefore, we obtained r1 of 0.62 (5/8) and r2 of 0.71 (5/7) where non retrieved reports were on areas. No reports were retrieved with keyword search because there were not any reports that contained all of the words within the query (i.e., lesion size greater than 10mm).

q4–Find all reports that contain a liver increased in size: In semantic search, reports were retrieved with p1 of 1 (7/7) and p2 of 0.86 (6/7). We got r1 of 0.78 (7/9) and r2 of 0.86 (6/7). Non-retrieved reports stated an increase in lobe size but not explicitly on liver size. Hence, these reports were not retrieved. Such logical implications can later be handled via rules expressed in Semantic Web Rule Language (SWRL) in ONLIRA. Here, we could formulate a rule as $Liver(?x) \wedge RightLobe(?y) \wedge size(?y,'increased') \implies size(?x,'increased')$. This rule states that if a size increase in right lobe is observed, then it can be concluded that the liver size has increased, too. In this way, we could make further inferences by using rules on top of ONLIRA.

In keyword search, a precision of 0.50 was observed (1/2). One report states that a liver has normal size but an increased density. This report was incorrectly retrieved as a result for this query, since the increase was not related to the liver. r1 was observed as 0.11 (1/9) and r2 as 0.14 (1/7). Recall values were low because in six reports, instead of the word ‘increase’ its synonym ‘enlarged’ had been used, and other reports were not retrieved because of logical implications mentioned earlier. It is possible to improve keyword search by including synonyms of each word, which may result in an increase in recall (since more documents will be matched) but possibly decrease of precision (some of the words may be matched for the wrong reason).

q5–Find all reports that contain hypodense areas: In semantic search, 11 reports were retrieved with a precision of 1 (11/11), r1 of 0.85 (11/13) and r2 of 0.69 (11/16). In non-retrieved reports, it was stated that the density was decreased and steatosis was observed which implied an hypodense density. This logical implication can also be handled with a semantic rule in ONLIRA. Only three reports were retrieved with a precision of 1 (3/3) with keyword search because lesions were not treated as areas i.e. reports including hypodense lesions were not retrieved. Hence, we observed r1 of 0.23 (3/13) and r2 of 0.19 (3/16). Overall, our results show that in all cases, semantic search performs either as good as or better than keyword search.

IV. Discussion

RadLex [7] is a language of radiology terms (>30,000 terms) developed to enable standardization among various software that use radiology terms. RadLex terms correspond to a dictionary of concepts. RadLex has been widely used in many successful applications, including systems to annotate and transform image markups [9] as well as retrieval engines that search through medical documents and images [10]. Unfortunately, relations of concepts are not always part of its description. For example, RadLex can express that a right lobe is a type of lobe, but cannot express that a right lobe can contain a lesion. Applications that use RadLex need to handle these relations in their own context; hence need to develop their own integrity checks to assure that statements make sense. With the use of an ontology, on the other hand, concepts can easily be related to each other as demonstrated in Section III. Furthermore, integrity and cardinality requirements can be specified and enforced for inferencing purposes. Therefore, the use of ontology, with concepts and their relations, is an important step towards developing applications that require semantic processing capabilities [11].

MEDICO consists of an image parsing system, a context-sensitive annotation tool, and a retrieval engine of medical images [12]. The MEDICO ontology uses the well-known FMA ontology and terminologies like RadLex and ICD-10. It is is used to represent extracted metadata from DICOM and medical annotations. The annotated images can be searched through keywords from the ontology. Their work focuses on automatically annotating parts of images with the corresponding ontology concepts. Our work focuses on the processing of ontologically structured reports. Presently, for the purposes of our work, the reports are manually created by radiologists via a form based reporting tool driven by ONLIRA. This tool provides generation of ONLIRA based instances. The presence of the relations and their constraints enable the inferences to be useful for intelligent processing, such as during retrieval (as outlined in the queries in Section III).

Gibaud *et al.* develop an application ontology (OntoVIP) to annotate, index and retrieve medical image simulation object models [13], which are then used to simulate medical images. Similar to our approach, they consider concepts and relations among concepts. However, their use of the ontology is different than ours since they use it to create simulation objects.

Sevenster *et al.* introduced an ontology-based technology that binds image and knowledge and evaluated it in the neuro-domain [14]. Their system allows a user to select a body part from an MR image and infers relevant information about the part using the well-known SNOMED CT ontology, among various other things. They experimentally show that this ontology-based approach achieves a high recall. Our experimental results are in line with this result, such that when the data is ontologically represented, recall increases.

To extract information from existing radiology reports retrospectively, Lacson *et al.* developed an ontology-utilizing toolkit in radiology domain [15]. They propose an information retrieval approach in the domain of radiology by augmenting a natural language processing engine with an ontology. The search queries are processed to obtain a set of keywords enhanced with similar words (based on existing dictionaries), which are then used to search through radiology reports. Query processing with enhancement yields better results than simple keyword search. Their work, unlike ours, does not focus on the specification and utilization of relations.

V. Conclusion

To demonstrate how the ontology can indeed be beneficial for semantic processing, we have first developed an ontology of liver for radiology. This ontology contains various concepts as well as their relationships. We have then demonstrated how this ontology can be used to express radiology reports with example statements from real radiological reports. Our experiments show that ONLIRA is capable of representing many useful statements. We have then studied the performance of searching ontology-based reports in comparison to searching free text reports using NLP techniques. Our results show that when radiology reports are ontology-based, information can be searched with both higher precision and higher recall. The major reason for this is that the semantic content of the reports, rather than just lexicons, is represented and semantically queried. Hence, information that cannot be captured with keywords can be queried successfully.

ONLIRA and its applications intend to serve as a proof of concept, which would require scaling up to the whole body and merged with a comprehensive ontology like RadLex. As shown in Section III there are still some important concepts that are not captured by the current version of ONLIRA. Gallbladder is one of them. Adding such important concepts and relations to ONLIRA will be our immediate next step. Presently, ONLIRA is utilized in a Web based data collection tool that has been developed as part of the CaReRa project. The liver

TABLE II: The recall and precision values for five queries for semantic search and keyword search. p1 and p2 are precision values, r1 and r2 are recall values computed according to the first and second radiologists, respectively.

Query ID	DL Query / Keyword Query	Semantic Search				Keyword Search		
		p1	p2	r1	r2	p1=p2	r1	r2
q1	DL query: Lesion Keywords: Lesion	1	1	0.80	0.86	1	0.80	0.86
q2	DL query: Lesion and isLocatedInSegment some (Segment and isLocatedInRegion value PosteriorRegion) Keywords: Lesion posterior	1	1	1	0.86	-	0	0
q3	DL query: Lesion and hasAreaLengthFirst some int[>10] Keywords: Lesion size greater than 10mm	1	1	0.62	0.71	-	0	0
q4	DL query: Liver and hasSizeChange value 'increased' Keywords: Liver size increase	1	0.86	0.78	0.86	0.50	0.11	0.14
q5	DL query: Area and hasAreaDensity value 'hypodense' Keywords: Area hypodense	1	1	0.85	0.69	1	0.23	0.19

imaging observations are collected based on ONLIRA. The most significant direction we are pursuing is the development of a model for semantic query handling, which shall expand or restrict queries over liver patients. The aim is to deliver a satisfactory set of similar cases given a particular liver patient case.

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