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INTEGRATION OF MEDICAL ONTOLOGY CONCEPTS TO ANNOTATE MEDICAL IMAGES

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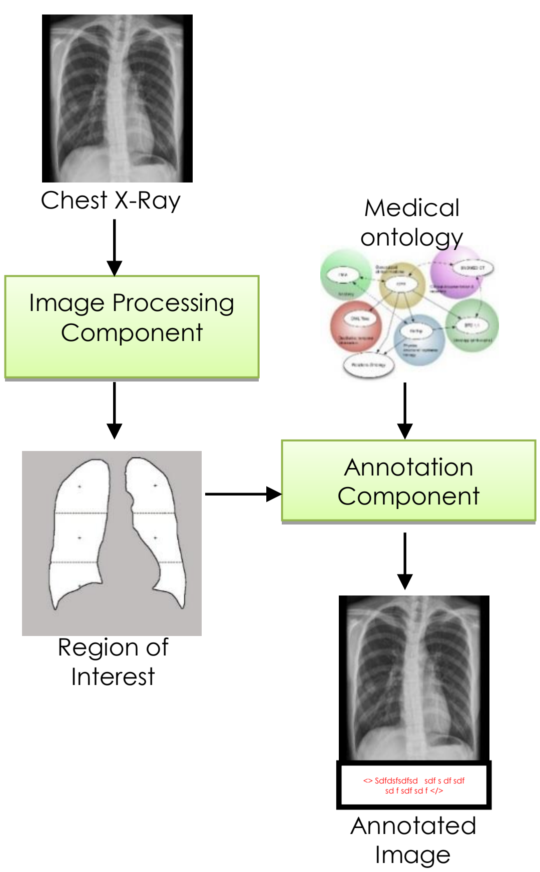
Graphical abstract



Abstract

Medical ontology has become an important element to enrich semantic description in medical images. The enrichment process can be done with medical image annotation where label or keyword can be added into the image description. Therefore, in this paper, we have proposed an annotation model that contains two components i.e. image processing and annotation component in order to annotate chest X-ray images with relevant medical ontology concepts. The first component helps transforming the original medical image into six regions of interest for the lung area while the second component prepares medical ontology concepts to annotate the derived regions. By annotating the chest X-ray images with medical ontology concepts, we hope to obtain better and accurate image retrieval.

Keywords: Medical ontology, image annotation, Chest X-ray image

Abstrak

Ontologi perubatan telah menjadi satu elemen yang penting dalam memperkayakan keterangan semantik bagi imej perubatan. Proses pengayaan ini boleh dilakukan melalui kaedah anotasi imej perubatan iaitu menambahkan label atau kata kunci kepada keterangan imej tersebut. Oleh itu, dalam artikel ini, kami mengusulkan model anotasi yang mempunyai dua buah komponen iaitu komponen pemprosesan imej dan komponen anotasi bagi menganotasi imej X-ray dada dengan konsep ontologi perubatan yang berkaitan. Komponen utama dapat menolong untuk menukarkan bentuk asal imej perubatan kepada enam rantau kepentingan bagi kawasan peparu seterusnya komponen kedua akan menyediakan konsep ontologi bagi menganotasi rantau yang telah dihasilkan. Dengan menganotasi imej X-ray dada ini menggunakan konsep ontologi perubatan yang sesuai, kami berharap dapat memperoleh dapatan semula imej yang lebih baik dan tepat.

Kata kunci: Ontologi perubatan, anotasi imej, imej X-ray dada

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1.0 INTRODUCTION

The famous ontology definition; "*an explicit specification of a conceptualization*" as defined by Thomas Grubber is actually referring an ontology as set of concepts and their interrelations in a specific domain [1]. The ontology has been proven to be a useful instrument for knowledge presentation and reasoning in many domains such as digital libraries, semantic web and personalized information management. In medical image retrieval or content based image retrieval (CBIR) in general, the usage of ontology can be regarded as the first step to close up the semantic gap which occurs from differences between the way human perceived and machine understanding [2]. The condition is factual because ontology has the potential to increase application inter-compatibility, provide cross model relationships to support reasoning, and consuming image annotation.

In the actual development of a CBIR application for medical image, the ontology alone is still insufficient because it need to be integrated with others for excellent retrieval result. Hence, this paper has highlighted our proposed model for the integration between ontology and image annotation. Either semi-automatic or fully automatic image annotation, the integration activity allows associating textual caption or keyword to the images and support coherent image description for better retrieval and most important; enriching the image meaning to reduce the semantic gap problem [3], [4].

The emergence of medical image modalities such as X-ray, Computer Tomography and Magnetic Resonance Imaging has increased the production of medical image hence doubling the annotation activities. There are lots of approaches used to annotate medical image as presented by prior researcher, however, in this paper, we concentrated on annotating ontology concepts with chest X-ray (CXR) images in lung area using spatial position. The spatial position can be extracted in images by using the spatial relationship extraction in two position conditions that are topological and directional [5]. Topological condition include spatial position like beside, disjoint, outside and cover meanwhile directional comprise spatial position such as left, right, upper and below.

Therefore, the main concern in our discussion is to propose the effective way to annotate the lung area in CXR images with medical ontology concepts. By applying this, we can enhance the expressivity of the annotated regions and at the meantime; the associated semantic vocabulary is controllable and may infer more related knowledge in medical. In order to discuss the issues further, the rest of the paper is presented as follow. Section 2 discusses the proposed method to annotate CXR image with medical ontology concepts while Section 3 elaborates the image processing component. Section 4 explains annotation components and later Section 5 describes the processes to annotate the CXR images with the medical ontologies in Afterward, Section 6 concludes our discussion.

2.0 PROPOSED MODEL FOR ANNOTATING CXR IMAGES WITH MEDICAL ONTOLOGY CONCEPTS

In order to integrate the medical ontology concepts with medical images via image annotation, the proposed model as shown in Figure 1 is drawn.

In the model, there are two components involved that are the image processing components and the annotation components. Briefly, the image processing component is used to transform the CXR image from its original appearance into region of interests (ROI) that contain only the lung area. Meanwhile the core items discussed in this paper; the annotation component, is used to annotate the ROI with relevant concepts found in the medical ontology regarding lung. The later sections will elaborate the two components in details.

3.0 IMAGE PROCESSING COMPONENT

The image processing component contains initial tasks that are needed to prepare the CXR images before they can be annotated with the medical ontology concepts. After executing these tasks, the actual CXR images will be transformed into a new look and suitable for the latter tasks. Therefore in the proposed model, three tasks, namely binary conversion, segmentation and feature extraction have been applied to the images so that at the end, the ROI of the extracted lung area can be derived.

The first task in the image processing phase is the binary image conversion. The task is straightforward and easy to be executed with the help of image processing tools where the actual CXR images are transformed from a grayscale image into binary image. In other word, the image's color depth is converted from 256 bits into 2 bits which caused reduction in the image's color into black and while only. When there are only two colors left, it helps to ease the process to identify the lung areas in the binary image.

Later, the lung area has to be segmented to isolate them from other anatomies. In general, segmentation is a systematic task to distinguish objects within an image into separate regions based on certain homogeneity measurement inside a single region [6]. Meanwhile in the field of medical image analysis, segmentation is used to delineate specific anatomical structures with the aim to diagnose various disorders, locate pathologies, create statistical atlases, and quantify structural properties

[7]. Segmented regions help researchers to apply further image analysis to the image hence this task is essential in image pre-processing phase.

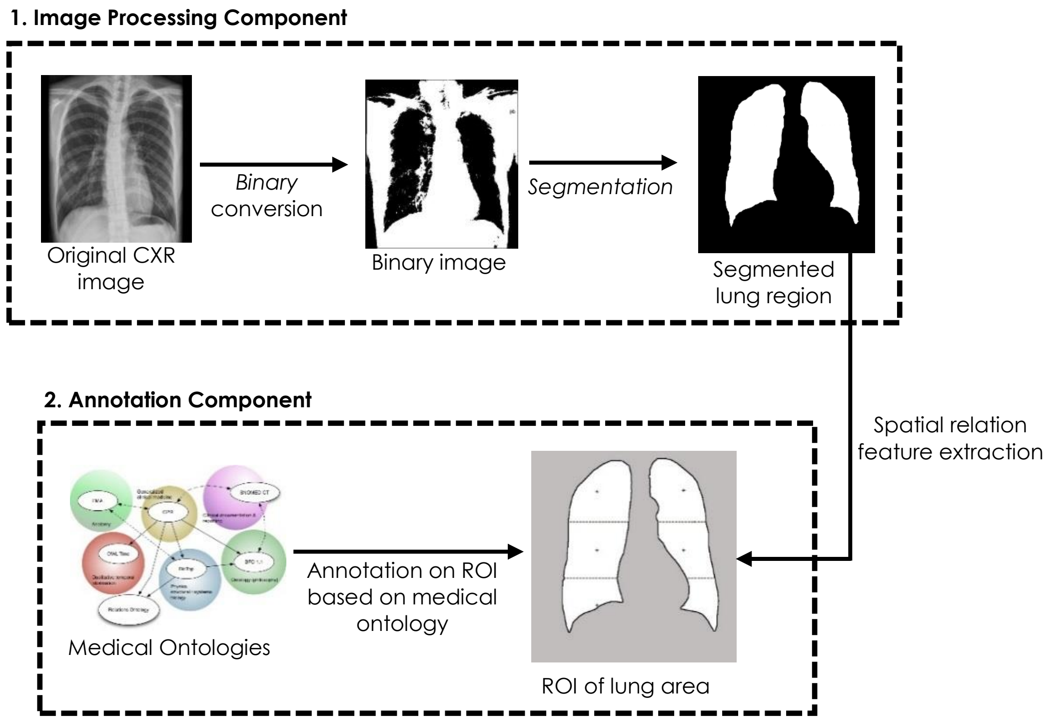

Figure 1 Proposed model to integrate medical ontology concepts with medical images

As far as our concerned, so far, there are two popular methods for image segmentation which include supervised, and unsupervised segmentation method.

Supervised image segmentation required some amount of images with desired output to be supplied as a mean to train the segmentation algorithm [8]. Afterwards, the trained algorithm is used to identify similar image features for further segmentation task to new images. This makes the methods versatile because each method can be applied to many different segmentation tasks, including the ones investigated here. On the contrary, unsupervised image segmentation does not required any output image to train the segmentation algorithm because the training part itself can be omitted [9]. Advanced image supplies is not a prerequisite in this method because image features can be acquired during the segmentation process. Rule-based schemes founded on method such as energy diffusion, graph partitioning and regions growing can be applied to acquire the image features [10]. Although the unsupervised method looks much easier, it has drawback as it is not flexible to handle multiple types of segmentation task. Furthermore, human intervention is still compulsory during the training process so that the segmentation task can become more accurate.

In [6], we have discussed our effort in segmenting CXR images based on unsupervised method namely using combination methods between edge detection and regions morphology. The idea to run the segmentation task is to isolate the lung area from other anatomies so that we can annotate it with relevant semantic description. In the paper we have showed that after the original CXR images are converted into binary image, the segmentation task can be done easily because the lung area can be seen straightforward as it is indicated by the dark area at the center of the image (see Figure 1). However, our segmentation output is not satisfying as the lung area is rounded with jagged edge as shown in Figure 2.

Figure 2 Our segmentation output as can be found in [6]

We suspected that this condition may happened due to lack of robustness from our segmentation algorithm to deal with unstable gray color distribution from the CXR image dataset that we used. Therefore, we recommended that one should try to use supervised segmentation method because based on our finding, this method outperformed the unsupervised method. We found out that in [8], three segmentation models namely Active Shape Model, Active Appearance Model and Pixel Classification have produced excellent segmentation output for the CXR images. Moreover, future researchers also can occupy these segmentation outputs effortlessly because they are accessible online via http://www.isi.uu.nl/Research/databases/SCR/index.php. By using the source, one can reduced the time to mess up with image pre-processing tasks so that more effort can be done to apply further image analysis to the segmented image.

After the lung area has been successfully segmented, it need to be divided into several regions. In this case, we recommended that future researchers should apply region of interest (ROI) technique as it is available in almost all image processing tools. Furthermore, the technique is very easy to apply and manage to divide segmented space like the lung area into portion of individual regions. According to our prior finding in [11], the division of lung area for the CXR images can be done based on radiologist practice to locate the nodule in lung. In their diagnosis, radiologist divided the lung area into six zones that are left upper zone, left middle zone, left lower zone, right upper zone, right middle zone and right lower zone. This division style helps them roughly to sense the nodule in the lung. Therefore, in the proposed method, the radiologist division method can be used as the basis to divide the lung area into ROI. Figure 3 shows the lung area division proposed by radiologist to detect the nodule in lung.

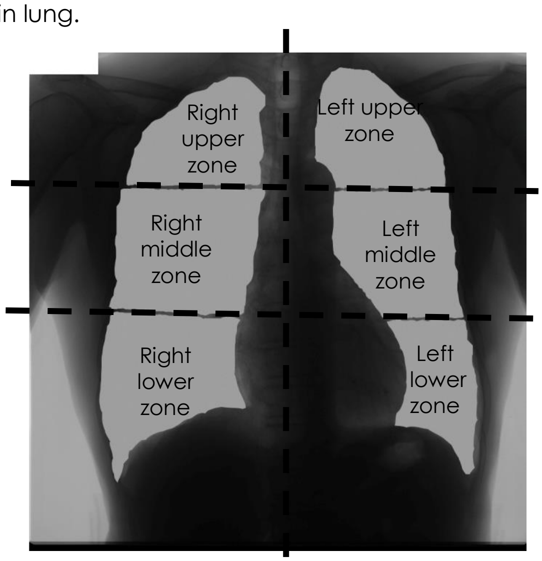

Figure 3 The lung area divisions into six regions as proposed by radiologist

At the end of the image processing tasks, six ROIs are generated in the lung area. Later, to establish the spatial relation among the ROIs, we proposed to use a local feature that can represent each ROI. The feature can represent the ROI either as a whole object or probably parts of the object. For instance, if a researcher want to present the ROI as a whole object, he can use method such as minimum bounding box which can covers the whole area of the ROI. Meanwhile if he think of presenting the local feature by using part(s) of the ROI, he can use simpler method such as centroid point and image patches (for instance using scale invariant feature transform (SIFT)). Spatial relation rules between each local feature can be designed so that it can interconnect each ROI together.

4.0 ANNOTATION COMPONENT

The annotation component is used to annotate medical images with concepts regarding lung from the medical ontology. Annotated images will contain high semantic description and shall improve the image retrieval process later via query statement. Therefore, after all image processing tasks completed, images need to be annotated with the medical ontology concepts.

At the moment, there are many medical ontologies available where each of them has their own features and suitable for certain medical concepts like anatomy, drugs, diseases and diagnosis [5]. As illustrated in Figure 1, our proposed model include medical ontologies to annotate the CXR images in general or specifically to the ROI of the lung. Based on our library research, we found out that there are at least two medical ontologies namely Foundation Model of Anatomy (FMA) and RadLex that are suitable to be chosen for the annotation task. FMA is an open source ontology generated by the University of Washington and concern about human body anatomy [12]. The ontology has numerous concepts of human body and it also contains well-structured relationships between instances of the concepts. Additionally, the ontology is also easy to explore and allows machine based system to extract its concepts based on its web ontology language (OWL) tags [13]. Meanwhile RadLex is closed type medical ontology and it is fully controlled by the Radiology Society of North America [14]. Although access to RadLex is not easy as FMA, the ontology contains more than 30,000 medical concepts that relates to anatomy, imaging technique and diagnostic images. Therefore, we recommended that these two ontologies should be combined so that we can obtained richer medical concepts from medical ontologies to annotate the lung area in the CXR images.

4.1 Combining FMA and Radlex

Prior the usage of relevant concepts from medical ontologies to annotate the CXR images, one has to look on at least on two issues regarding the matter. Firstly, how to combine the medical ontologies (FMA and RadLex in this case) and secondly how to build those ontology and use them in the application developed.

In order to tackle the first issue, firstly, we have to bear in mind that medical ontologies in general contains huge number of concepts and terms. It is not appropriate to select all concepts as it can caused bundle of unrelated concepts plus there will be redundancy of concepts since we want two combine two ontologies together. Therefore, we must decide what type of concepts to choose so that we can focus and work only on this concept. For instance, in the proposed model, we wanted to annotate the image with spatial relationship concept for the lung area, therefore any terms related to **lung** and **pulmonary** should be prioritized while other terms can be ignored. Secondly, when the required concepts involved more than one ontology and combining these ontologies are compulsory, we need for methods to create modular and manageable application ontologies by piecing together components derived from multiple sources, especially from domain reference ontologies which can support all sorts of applications that pertain to the corresponding domains [15]. Figure 4 show how [15] combined the FMA and RadLex ontology to create an application ontology for anatomy.

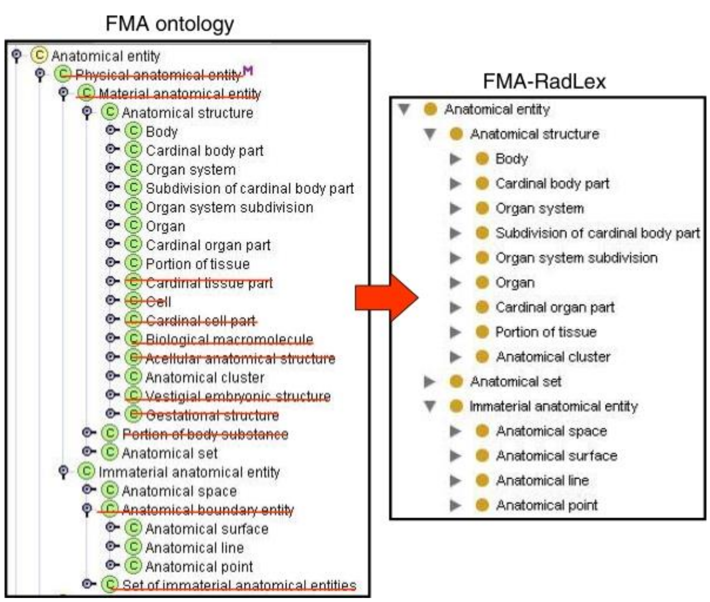

Figure 4 Combining the FMA and RadLex ontology as done in [15]

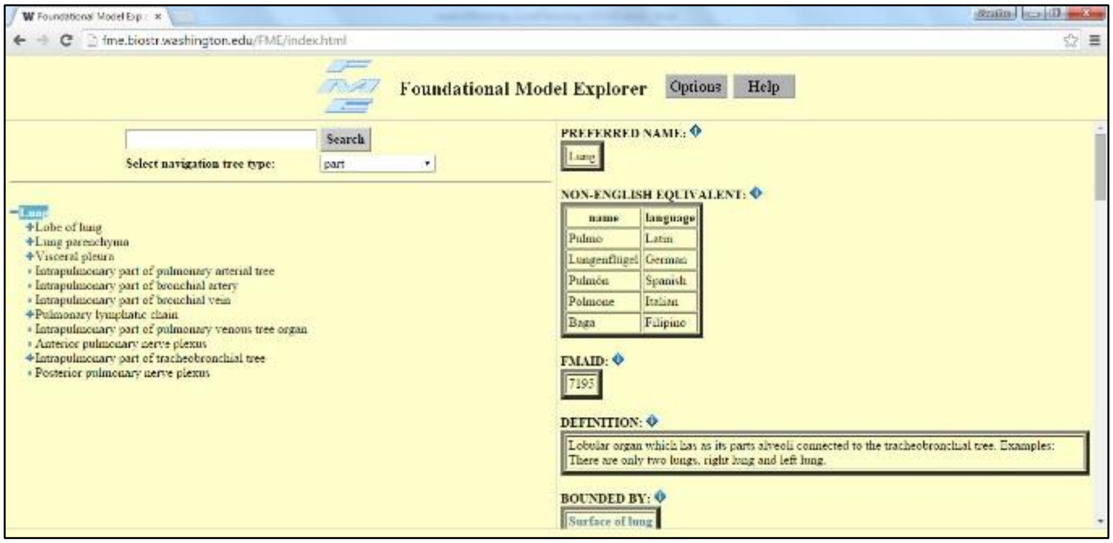

Figure 5 FMA Explorer

Once the first issue solved, the second issue that need to be highlighted is the way to build the ontology so that it can work well with the application develop. In this matter, it is found that there are at least three methods to build or occupy ontology for any application. The option for the methods include hard-coding the ontology elements within the application, embedding the ontology in the local system or incorporate into the application the ability to contact (via standard web protocols) a remote server hosting an ontology source [16].

Building an ontology with hard-coding means to play around with the common method of building application in the traditional way with lots of computer code and build and compile activities. This option required excellent technical skill and knowledge to understand the programming language as well as the ontology development so that the ontology can be successfully build and later, used with the application. At the current moment, this method is not the best option to choose as easier mode can be implemented to develop the ontology.

Therefore, in the second option, we can just download the ontology and embed it into the application which is located in the local system and used them directly. Medical ontology like the FMA can be downloaded and installed into the local system with minimum authentication requirement. The best part of this method is that the ontology content (concepts, terms and relationship) can be modified. The modification can be done using ontology editor like Protégé so that the ontology content only contains specific features needed. By applying the second method, the time taken to develop the ontology from stretch can be used with the other important task like defining the correct class, creating required instance and building the actual relationships between instances.

The continuing evolution of the Semantic Web has enable integration between users application with the ontology via Internet connection to the remote server hosting the ontology source. This situation offers application developers the flexibility to be anywhere at any time to connect their system with the ontology source. Furthermore, since the application can link with the ontology source directly via Internet, there is no need to load the entire ontology at once and the space taken to install the ontology into the local system can be reduced. Additionally, application developers can ignore the restless job of continuously updating the ontology because normally this process will be done by the bodies that control the ontology sources. Therefore, some medical ontology like FMA has introduced FMA Explorer; as shown in Figure 5, as a mean to enable researcher to access the content via web.

The FMA Explorer enables researchers to link their system with the ontology content online so that the annotation process can be done easier. Researchers do not need to hesitate updating the ontology because any changes regarding the ontology content will be done by FMA committee themselves.

5.0 ANNOTATION ON THE CXR IMAGES WITH MEDICAL ONTOLOGY CONCEPTS

After the second issue solved, the next task is to annotate the CXR image with the concepts from the ontologies. The annotation task for CXR images can be done in two methods that include guided annotation or automatic annotation [17].

The guided annotation or semi-automatic annotation is a task that enable application developers or users to have fully controlled ability of selecting the suitable type of medical ontology concepts to annotate the images. In our proposed model case, this means that he can decide what concepts or terms should be used to label the ROI of the lung. This task can be simply done with interactive activities like pull-down menu, selecting the option button or text insertion to choose the correct ontology concept for the images. With this method, the annotation will be accurate and precise if the user is an expert (like radiologist) because he knows exactly what concepts to choose for the images. Conversely, annotated images will struggled with imprecise information if non-expert users involved. From our limited knowledge regarding the semi-automatic annotation tools, we discovered that at least two excellent tools can be tried out to annotate the image. LabelMe is a database and an online annotation tool that allows the sharing of images and annotations among multiple web users [18]. Apart from that, the tool also provides functionalities such as drawing polygons, querying images, and browsing the database. From our experience using this tool, we can simply annotate any image just by drawing polygons around the object as its boundaries, and later, labelled the object using suitable description. The description can be based on words that are available in WordNet. There are also image datasets that have already annotated by other users and ready to be used for research purposes. However, from our concerned, there is no comprehensive dataset for CXR images available in LabelMe database. Figure 6 shows snapshot of LabelMe as illustrated in [18].

Another excellent annotation tools that is available is M-OntoMat-Annotizer 2.0. Similar to LableMe, this annotation tool is also a research based tool developed within aceMedia Integrated Project [19]. The tool supports automatic segmentation and annotation at segment and image level. Additionally, the annotation task concerns the assignment of domain ontology concepts to image segments or images.

Figure 6 Snapshot of LabelMe

Meanwhile, for the automatic image annotation, we can occupy machine learning techniques like support vector machine, decision tree or neural network to acquire decision for the best ontology concepts to choose based on certain image features. These techniques have been proven in other image related applications like classification and clustering. With automatic image annotation, we can minimized human intervention therefore reducing misguided interpretation towards objects description within an image. The correct annotation decision will be only finalized based on criteria that have been specified for the images. However, issues like the precision of the machine learning technique and the amount of required images features should be focused because they can influence the capability of the technique to decide the best decision.

6.0 CONCLUSION

In this paper, we have discussed the proposed method to annotate CXR images with ontology concepts for the ROI in the lung area. Realizing the importance of the annotation task, this paper is published. We have discussed our proposed model based on two important annotation components that are the image processing components and the annotation components. The image processing components prepare the image into suitable form i.e. six regions of lung area while the annotation components produced the way to annotate the image with relevant medical ontologies concepts. Later, based on the suitable concepts from the ontology, annotation task can be performed to the selected CXR images. We believed that well annotated medical image increased the sematic description of the images and as a result helps the image retrieval process when these images are needed.

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