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DIGITAL IMAGE COLLECTION TECHNIQUES FROM PACS TO MAKE A DEEP LEARNING APPLICATION FOR CARDIOMEGALI DETECTION

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ABSTRACT

Picture Archiving and Communication System (PACS) in digital images functions as a system which can retrieve, archive, display and process digital images. PACS management is well supported by with digital modalities, the number of examinations continues to increase, there is a potential for the availability of large digital image data (big data). The availability of big data radiological images opens up opportunities for development Artificial Intelligence (AI) with deep learning method. An example of using deep learning in radiology is the automatic detection of the size of the heart, whether it is classified as cardiomegaly or whether the heart is normal from a thoracic image. Before making a deep learning application, it is necessary to know how PACS works where we retrieve data, how the process of retrieval and classification of thoracic image data from PACS. This paper is sourced from the literature review and the results of observations following clinical practice at Dr. Cipto Mangunkusumo Hospital. Observations made from clinical practice, PACS has functioned as a place to archive, display, print and send radiology digital images. Digital image data collection from PACS, through the process of data classification, tabulation, identification, image retrieval and data grouping, is the first step for making deep learning programs. The conclusion that can be drawn is that PACS is a large source of digital image data, good data retrieval and initial data classification techniques will facilitate and improve the performance of deep learning creation.

Keywords: PACS; Deep Learning; Cardiomegaly; Classification.

Introduction

Cardiomegaly is known as heart enlargement, heart enlargement is not a disease, but rather a sign of a condition of abnormalities associated with cardiovascular disease[1]. The heart experiences enlargement can be caused by a pressure load or an increase in volume (volume overload) which then has an impact on increasing the pressure of the heart wall.

Several diagnostic examinations of the heart organs to determine the enlargement of the heart and its causes, including thoracic radiographic examination. Thoracic radiographic examination is useful in showing the anatomical structure of the

thorax[2] including the lungs and heart, thoracic examination can also be used to evaluate the size and structure of the heart. Thoracic radiographic examination is one of the low-cost diagnostic modalities and is available in many health services[1,3]. From thoracic radiographic images, radiologists use CTR (Cardiothoracic Ratio) as a measurement scale to determine the abnormality of heart size or the presence of indications of cardiomegaly[4]. The accuracy of using CTR (Cardiothoracic Ratio) to detect an increase in heart size and predict cardiomegaly is 95.8%[5]. This measurement method is carried out conventionally, CTR is obtained by calculating the ratio between the longest width of the heart compared to the maximum thoracic diameter measured from the rib boundary[6].

Rapidly developing digitalization technology supported by information and communication technology accelerates the development of digital transformation of the industrial order[7]. Digitalization in the field of radiology is growing rapidly along with the development of radiology modalities and Picture Archiving and Communication Systems (PACS).

Digital radiography according to the American Association of Physicists in Medicine (AAPM) is an imaging technique that uses digital detectors to convert X-rays passing through the patient's body into electronic signals (analog signals), then converted into digital data for computer processing, digital processing techniques are useful for improving the interpretation of radiological images diagnostics[8].

Digital radiography that exists today includes Computed Radiography (CR) and Digital Radiography (DR). Computed Radiography (CR) was developed to have similarities to film-based radiography, in which tapes are physically carried from an X-ray machine to a processing machine called a CR reader. The CR system utilizes photostimulable or phosphorus storage to produce digital images, the crystals inside contain several materials such as barium fluorohalide with europium (BaFBr : Eu or BaFI : Eu). Phosphorus crystals are formed into resinous plates in an unstructured manner. This material emits light after X-ray exposure, but these phosphor crystals can also emit light a little later when exposed to different light sources. Such a process is called Photostimulable Luminescence (PSL). Barium fluorohalide is coated on plates that serve to protect it from damage and exposure to foreign objects. This material has come to be known as a digital detector or imaging plate in CR.

Digital Radiography (DR) has the ability to capture, process, and display initial images in a single unit of modality of the tool itself. The detector on the DR tool is directly connected to the digital processor, so the radiographic image can be immediately sent for processing as soon as the inspection is performed. In terms of image processing in the detector DR is divided into direct conversion DR and indirect conversion DR[9].

Digital image is a representation of the patient's numerical matrix value[8] that can be stored in computer memory. Digital images can be stored and accessed at any time, this benefits patient diagnostics and is useful for learning and research, in addition to the rapid distribution of radiographic images between units in the hospital without the risk of losing the image itself. Digital image quality has a wider exposure range than film screen radiography, the dynamic range of digital detectors is greater thus reducing X-ray exposure in patients[10]. A commonly used format in medical digital imagery is DICOM (Digital Imaging and Communications in Medicine), an international format used to transmit, store, retrieve, print, process, display and transmit information in all aspects of digital medical

imaging. Format DICOM not only functions to store images, but also stores data on other image-related parameters such as the patient's 3D position, the size of the objects in the image, the thickness of the slice, the parameters of the image exposure and storage in DICOM format no image information is lost.

The resulting digital image requires a single system that can retrieve, archive, display and process digital images derived from many modalities known as Picture Archiving and Communication Systems (PACS)[11]. Without PACS, digital modalities will act like analog modalities that require printing films for the process of reading photos and delivering results to patients. With PACS, digital images can be stored in large quantities known as big data, it will be very useful for training, education[12] and the development of science in the field of radiology including radiographers.

Computed Radiography (CR) and Digital Radiography (DR) technology or the use of PACS is equipped with a CTR measuring device on thoracic images but is done manually. Manual CTR measurements as well as manual labeling of organ boundaries will be prone to errors and cause misinterpretation of readings[13]. The use of Artificial Intelligence (AI) technology with the Deep Learning (DL) method provides a solution by automatically classifying the size of the heart, into the category of cardiomegaly or heart with a normal size. Latest advances in AI with DL improve performance significantly in computer-aided cardiomegaly detection to a level comparable to radiologists[14].

The deep learning method works by training computers to have the ability to study given data and produce human interpretations, with the aim that machines make it possible to analyze, process and understand digital data, recognize patterns in images and make diagnosis predictions by teaching computers through repetitive algorithms. DL has been widely used including for automatic object detection, image segmentation, automatic speech recognition, robotics [15,16]

Deep learning applications require large image data[17], for the detection of cardiomegaly this requires thoracic digital image data with a large amount of cardiomegaly heart and normal heart condition, with the presence of PACS is very helpful in providing this data. This large amount of data will be used as training data for making deep learning applications and deep learning accuracy test data itself. Therefore, it is necessary to take thoracic image data from PACS properly, to be prepared as training data and test data for making deep learning applications.

Methods

This paper aims to explain the use of PACS to create deep learning programs for automatic detection of cardiomegaly conditions in thoracic imagery. The explanation in this paper will be related to the technique of retrieving and classifying thoracic image data needed for deep learning. This paper was prepared with literature reviews, observations, and documentation in the field during clinical practice at Dr. Cipto Mangunkusumo Hospital Jakarta.

Results and Discussion

Radiology, which is a place for fieldwork practice, is a type A hospital, located in the Jakarta area. As a type A hospital, which also functions as a referral hospital, various digitalization-based radiology modalities are available here, from digital radiography which includes Computed Radiography (CR) and Digital Radiography (DR), digital fluoroscopy, computed tomography scanning or known as CT Scan, Ultrasonography (USG), Magnetic

Resonance Imaging (MRI), Bone Mineral Densitometry (BMD) and nuclear medicine, all of these modalities are connected together to the PACS facility that has been installed since 2012. The available PACS has been functioned optimally, including:

1. Archiving/saving digital images

   Digital images generated from various modalities are sent to PACS for storage and subsequent processing. The data stored in PACS includes a digital image of the radiological examination results, the patient's personal data, the time of sending the image to PACS, the radiologist's reading results and the name of the radiologist who performed the image reading. Each digital image derived from the modality has a unique code according to the medical record number of the patient.
2. Display digital imagery

   PACS can function to display the digital image in it again. The process of displaying this digital image is by entering a unique code in the form of a medical record number from the patient. This function is often used in connection with the process of reading images performed by radiologists.

3. Perform the digital image process

   PACS also functions to carry out the process of improving digital images, including the process of changing density, contrast, magnification, sharpening images, cropping and other digital processes.
4. Print digital imagery

   PACS functions to print digital images, print results in the form of films and CDs to be given to patients. The provision of printed results in the form of CDs and films is only intended for patients who will continue treatment at other health facilities, if the patient is still undergoing treatment at this hospital, then the results of digital images and readings of radiology results from PACS are sent to the Hospital Information System (HIS).
5. Submit an image to HIS

   PACS in radiology is connected to the digital information system found in the hospital. After the patient's digital image is read by the radiologist, automatically the reading results and digital images are sent to HIS owned by the hospital, the data sent to HIS is in accordance with the medical record number owned, so that the image and reading results immediately appear in the patient's data.

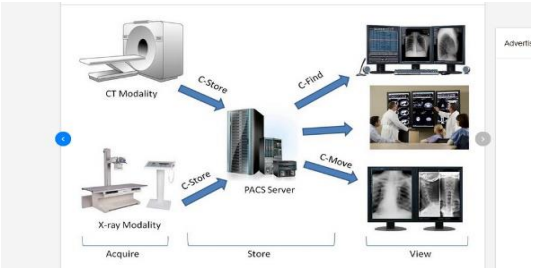


Figure 1. PACS function workflow [18]

With a complete digital modality, a large frequency of patient visits, good and long-standing use of the PACS system, it is certain that there is a huge potential for digital image data (big data). Potential data includes:

1. Volume

   Using the PACS system from 2012 until now the amount of patient data stored will continue to grow over time. This is a potential for data collection in the form of large amounts of digital imagery or known as big data.
2. Variations

   Using the PACS system from 2012 until now, the variety of stored patient data will continue to grow over time. This variation can be in the form of types of images according to existing modalities including radiographic

images, fluoroscopic images, mammography images, CT Scan images, MRI images, USG images, BMD images and nuclear medicine images. Other variations can be images based on the organ being examined or images that vary based on pathology.

3. Speed

   Digital image data can be retrieved and displayed quickly using the PACS system, by entering a unique data number in the form of a patient's medical record number. This is very useful if we need a history of patient data both new and old.

4. Correctness

   Correctness in this case refers to data sources and patient images that affect accuracy, such as inconsistencies, missing data, ambiguity, manipulation. The truth in the medical image becomes something that is very concerned, because this is where the process of treatment, treatment, follow-up of the patient's medical treatment depends on the digital image produced.

5. Value

   The data available in PACS in the form of images and other data is an extraordinary potential that can be utilized, both in terms of data statistics, utilization in the world of education, or in terms of developing digital radiology technology based on artificial intelligence.

As already outlined how PACS is functioned to its full potential especially the function of storing and sending images. As well as the potential that PACS has to store large amounts of data, varies and has speed in data processing for the development of technology in the field of digital radiology based on artificial intelligence. Likewise, artificial intelligence technology through the ability to read and process data, is able to carry out so much data analysis in a faster time[19].

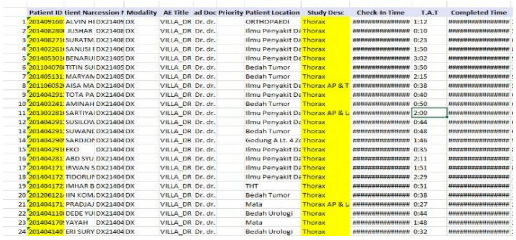
One of the applications of artificial intelligence with deep learning methods that utilize medical images from digital radiography, is automatic detection to determine heart enlargement (cardiomegaly). To create a deep learning application for cardiomegaly detection, a large number of thoracic images are needed which will be used as training data and test data. The function of training data in deep learning programs is to process imaging data with different levels of abstraction, allowing for DL to recognize and study large data sets as well as find complex patterns and patterns structures that can be used to predict something we want[20]. No restrictions Regarding the number of images needed for training data, the more images used for deep learning creation training data, the better the deep learning program that produces. Data test is used to conduct a series of tests on deep learning programs that have been made, from the deep learning program testing will be obtained the value of precision, sensitivity, specificity, positive guess value and negative guess value, which will reflect the effectiveness of the deep learning program made in classifying the heart whether cardiomegaly or normal heart. Therefore, it is very important to take thoracic image data properly and correctly sourced from PACS, because it will affect the performance of deep learning applications.

Requires a large amount of thoracic image data taken from PACS, this data will be used as a data set both as test data and as training data to create a cardiomegaly detection deep learning application. Techniques and processes of data retrieval from PACS:

1. Perform data classification

   Research data is retrospective collected from the Picture Archiving

and Communication System (PACS) with a range from 2013 to 2021. PACS contains a variety of images of various modalities and variations of examination. To facilitate the capture of thoracic imagery, data screening is carried out based on the type of examination and modality carried out at PACS. For the choice of modalities selected modalities CR and DR, for examination selected thoracic, and to make light data retrieval is carried out per year. If we want a thoracic photo that is only read by a certain doctor, data filtering can also be done based on the doctor reading thoracic image. For the creation of deep learning cardiomegaly detection data taken from 2013 to 2021.



	Patient ID	tient Narcession	Modality	AE Title	ad Doc	Priority	Patient Location	Study Desc	Check-In Time	T.A.T	Completed Time
1	201409160	ALVIN HI	DX	21408 DX			ORTHOPAEDI	Thorax	##########	1:12	##########
2	201408289	JUSMAR	DX	21408 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	0:10	##########
3	201408273	SUKATM	DX	21408 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	0:23	##########
4	201402203	SANUSI I	DX	21406 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	1:00	##########
5	201405301	BENARUI	DX	21405 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	3:02	##########
6	201104078	TITIN SU	DX	21405 DX	VILLA_DR	Dr. dr.	Bedah Tumor	Thorax	##########	3:50	##########
7	201405131	MARYAN	DX	21405 DX	VILLA_DR	Dr. dr.	Bedah Tumor	Thorax	##########	2:15	##########
8	201106052	AISA MA	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax AP & T	##########	0:38	##########
9	201404291	TOTA PA	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	0:40	##########
10	201402241	AMINAH	DX	21404 DX	VILLA_DR	Dr. dr.	Bedah Tumor	Thorax	##########	0:50	##########
11	201302891	SARTIYA	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax AP & L	##########	2:00	##########
12	201404291	SUSILOW	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	0:44	##########
13	201404291	SUWANE	DX	21404 DX	VILLA_DR	Dr. dr.	Bedah Tumor	Thorax	##########	0:48	##########
14	201404298	SAKIDIP	DX	21404 DX	VILLA_DR	Dr. dr.	Gedung A Lt. 4 Zi	Thorax	##########	1:46	##########
15	201404291	EKO	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	0:55	##########
16	201404281	ABD SYU	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	2:11	##########
17	201404171	HIVIAN S	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	1:51	##########
18	201404172	TIDORUF	DX	21404 DX	VILLA_DR	Dr. dr.	Ilmu Penyakit Da	Thorax	##########	2:29	##########
19	201404172	IMHAR B	DX	21404 DX	VILLA_DR	Dr. dr.	TNT	Thorax	##########	0:51	##########
20	201206121	IIN KOM	DX	21404 DX	VILLA_DR	Dr. dr.	Bedah Tumor	Thorax	##########	0:38	##########
21	201404171	PRADIAJ	DX	21404 DX	VILLA_DR	Dr. dr.	Mata	Thorax AP & L	##########	0:27	##########
22	201404118	DEDE YU	DX	21404 DX	VILLA_DR	Dr. dr.	Bedah Urologi	Thorax	##########	0:44	##########
23	201404170	YAYAH	DX	21404 DX	VILLA_DR	Dr. dr.	Mata	Thorax	##########	1:48	##########
24	201404140	ERI SURY	DX	21404 DX	VILLA_DR	Dr. dr.	Bedah Urologi	Thorax	##########	0:32	##########

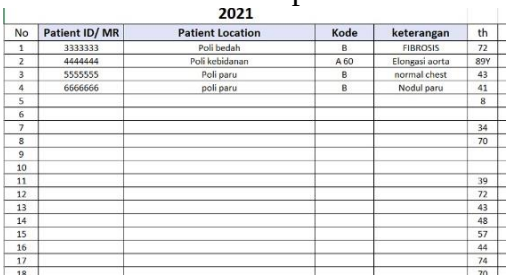
Figure 2. Filtering of Thoracic Image Specific Data

2. Tabulating

Method to facilitate and streamline the work, every year a table is made containing the image number code, medical record number, the patient's origin for treatment, a blank table prepared to fill in the tropic size of the patient's cardiomegaly heart condition or not, and additional information. The patient's abnormalities were taken from the radiologist's readings.

3. Identifying readings of the thoracic image

Table that has been made, using the medical record number, we identify the size of the patient's heart, if the cardiomegaly patient we code A and if the patient with a normal heart we give it a code B. and if there are other abnormalities in the thoracic image readings such as pneumonia, metastasis is added to the information column that has been provided.



2021

No	Patient ID/ MR	Patient Location	Kode	keterangan	th
1	3333333	Poli bedah	B	FIBROSIS	72
2	4444444	Poli kebidanan	A 60	Elongasi aorta	89Y
3	5555555	Poli paru	B	normal chest	43
4	6666666	poli paru	B	Nodul paru	41
5					8
6					
7					34
8					70
9					
10					
11					39
12					72
13					43
14					48
15					57
16					44
17					74
18					20

Figure 3. Example of the results of the identification of thoracic image readings

4. Thoracic imagery capture from PACS

Based on the table data that has been identified as the size of the heart, thoracic image is taken and reading data radiologist from PACS. Thoracic imagery taken in the form of DICOM and JPEG, DICOM form thoracic image that we will use as training data and test data, while thoracic image in JPEG form to help identify thoracic imagery, in taking thoracic imagery patient data and hospital data are first eliminated. The radiologist's reading data is taken in JPEG format, containing readings of thoracic imagery that can be used to verify the correctness of the patient's data. In retrieving and storing images, naming each thoracic image is carried out, based on the data number that has been prepared in the tabulation process plus code A in front of it for thoracic images with a cardiomegaly heart and code B in front of the data number for thoracic images with a normal heart.

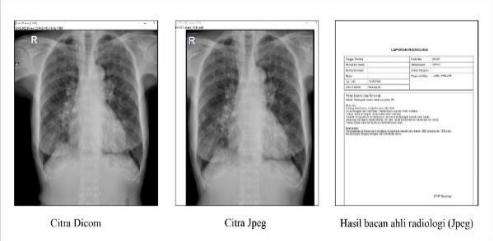


Figure 4. Example of a Thoracic Folder with Cardiomegaly

5. Group data in one folder

   Thoracic digital imagery and reading data are separated by the names of the cardiomegaly and normal heart folders. The cardiomegaly folder is for cardiomegaly images and the normal folder is for images whose heart is not cardiomegaly.
6. Classification of training data and test data

   Also prepared folders for training data and test data, the amount of test data is adjusted to the needs of the test, must be represented thoracic image with cardiomegaly heart reading results and thoracic image with non-cardiomegaly cardiac readings.

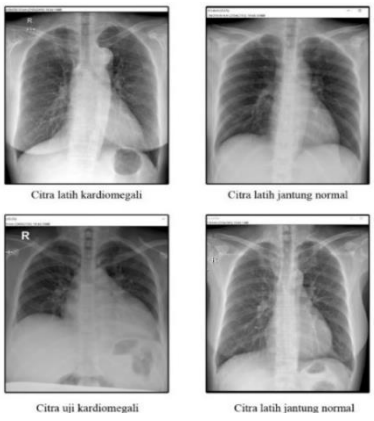


Figure 5. Example of Training and Test Data Folder Based on Heart Condition

Until this stage, the process of collecting thoracic image data needed for training data and test data can be said to be complete, thoracic image data is ready to be used for making deep learning applications for cardiomegaly detection.

Conclusion

The era of modern digital-based radiology, the existence of PACS is very important, the support of digital-based modalities and an adequate number of patients make the availability of digital image data in large quantities. This is an extraordinary potential that can be utilized, both in terms of data statistics, utilization in the world of education, or in terms of developing digital radiology technology. The development of AI-based diagnostics with deep learning methods can be so developed with the support of big data contained in PACS. One of the uses of the DL method in the field of radiology is the use of DL for automatic cardiomegaly detection, data collection techniques from PACS will well support the generation of AI with deep learning methods for cardiomegaly detection. It can be ascertained with the support of big data contained in PACS, the creation of deep learning programs to Automatic detection of other abnormalities can be carried out.

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