AI in Medical Imaging

Hieu Pham, Department of Medical Imaging,
Vingroup Big Data Institute (VinBigdata)

Ninh Binh 21/04/2021

Contents

What is Medical Imaging?

Medical imaging refers to techniques and processes used to create images of various parts of the human body for diagnostic and treatment purposes.

First medical X-ray by Wilhelm Röntgen of his wife Anna Bertha Ludwig's hand (Wikipedia).

Applications of X-rays

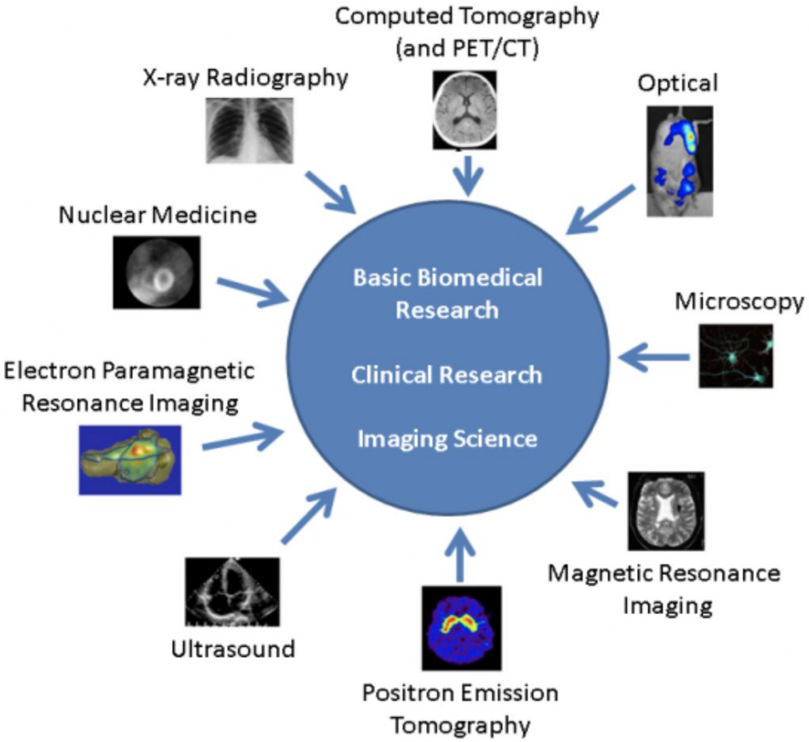
- X-rays soon became an important diagnostic tool in medicine, allowing doctors to see inside the human body for the first time without surgery.

- In 1897, X-rays were first used on a military battlefield, during the Balkan War, to find bullets and broken bones inside patients.

A fracture observed from an X-ray (https://radiopaedia.org/)

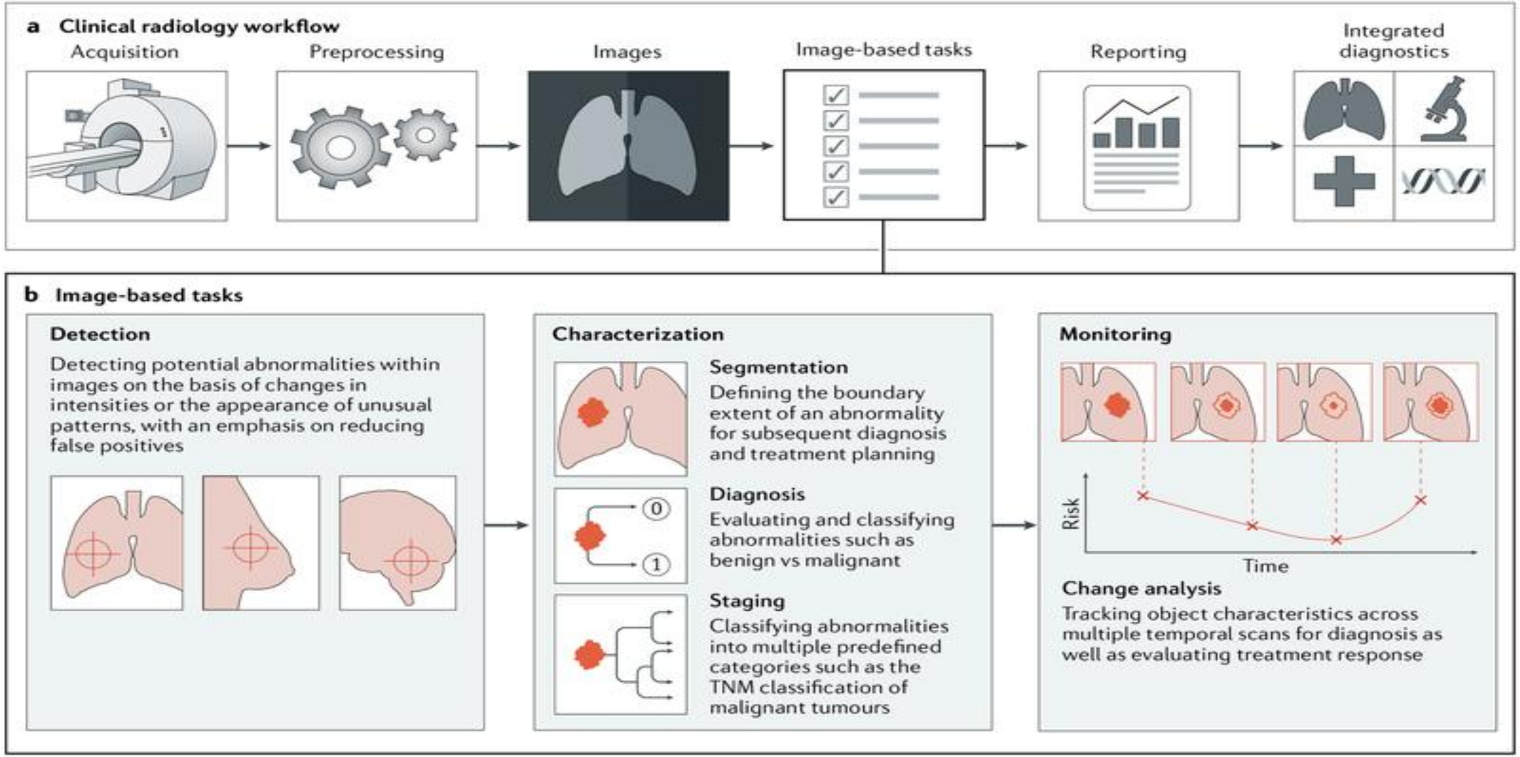
Imaging modalities

- X-ray radiography
- Magnetic resonance imaging (MRI)
- Ultrasound
- Endoscopy
- Positron emission tomography (PET)



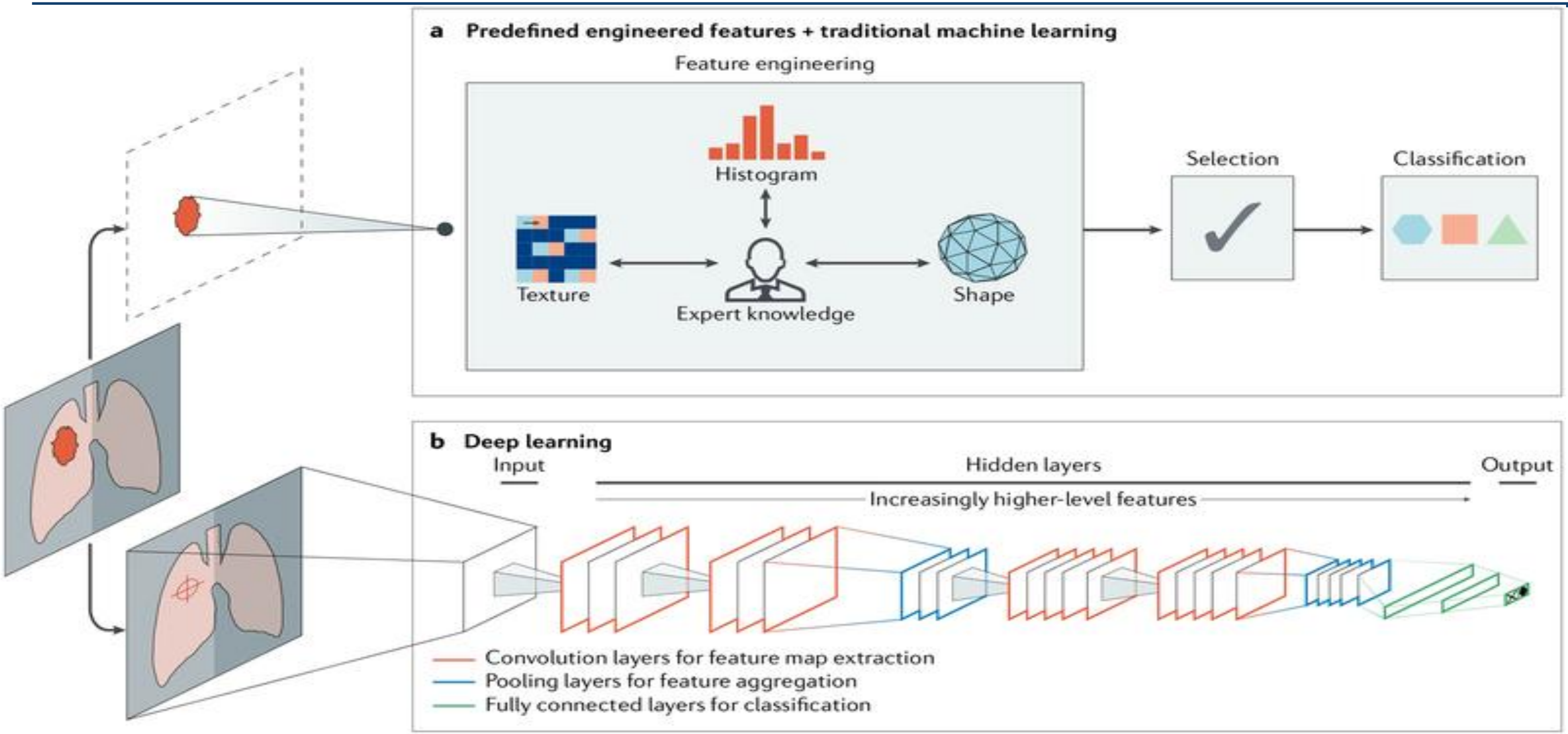
Sourced from https://radiology.uchicago.edu/research

Medical AI



The figure was sourced from Ahmed Hosny *et al.* ‘Artificial Intelligence in Radiology’, *Nat Rev Cancer,* 2018

Medical AI



The figure was sourced from Ahmed Hosny *et al.* ‘Artificial Intelligence in Radiology’, *Nat Rev Cancer*, 2018

Traditional AI approaches

- Traditional AI methods rely largely on predefined engineered feature algorithms based on expert knowledge.
- Such features are designed to quantify specific radiographic characteristics, such as the 3D shape of a tumour or the texture and distribution of pixel intensities (histogram).
- Examples of these models include Support Vector Machines (SVM) and Random Forests.

Deep learning approaches

- Learn automatically hidden representations from data to make decisions.

The rise of AI/Deep Learning in Medical Imaging

MICCAI 2018 paper statistics

- International Conference on Medical Image Computing and Computer Assisted Intervention - MICCAI (top conference in medical imaging)
- >1,600 attendees
- >1,300 submission
- +33%

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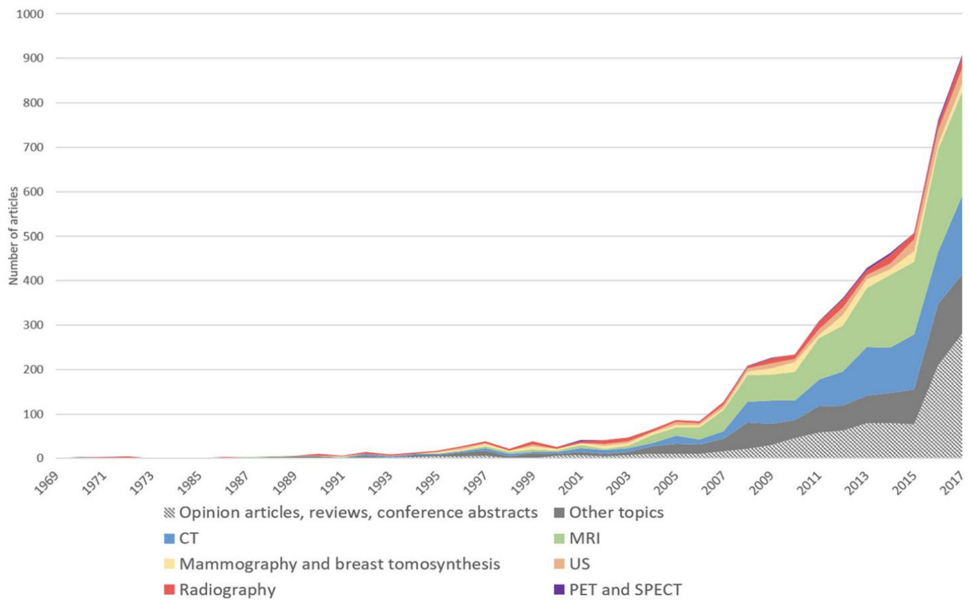
The rise of AI/Deep Learning in Medical Imaging



Number of publications indexed by EMBASE obtained using the search query “Machine learning OR Deep learning AND Medical Imaging”. Pesapane *et al*. "Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine." *European Radiology Experimental* 2.1 (2018)

Medical AI

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Medical AI startups

Sourced from https://medium.datadriveninvestor.com/

Recent advances in Medical AI

Current state of Medical AI

- 2012 ImageNet competition: AlexNet gave a dramatic decrease in image classification error rate.
- 2016 Geoffrey Hinton, the godfather of neural networks, said that it's “quite obvious that we should stop training radiologists”.
- Last 3 - 5 years: Increased activities in development of AI for radiology.
- For narrow-based tasks, the accuracy rates of deep CNNs surpass those human.

Recent advances in Medical AI

Some case studies

- Lung nodule detection (phát hiện nốt mờ phổi)
- Breast cancer detection (phát hiện ung thư vú)
- Diabetic retinopathy detection (phát hiện bệnh võng mạc tiểu đường)

Recent advances in Medical AI

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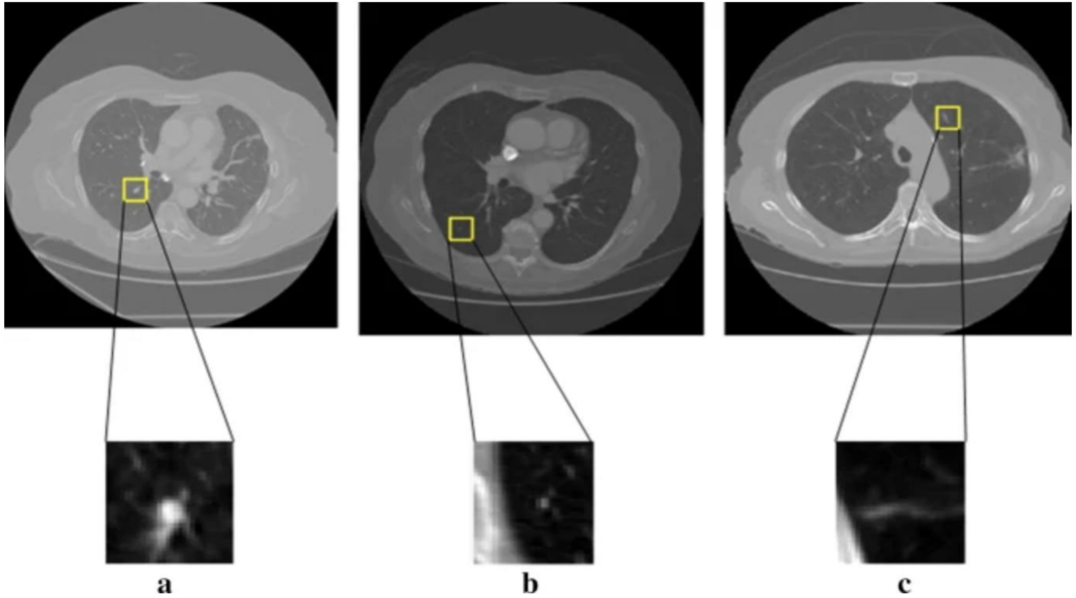
Lung nodule detection

- An estimated 222,500 people have been diagnosed with lung cancer.
- The 5-year survival rate for lung cancer is less than 20%, the 1-year survival rate is less than 50%.
- Low-dose CT screening for lung cancer in individuals is considered as an effective way of early detection.
- Interpreting CT scans for nodule detection is a challenging task/prone to error, which requires in-depth understanding of radiologic signs in thoracic imaging.

A physician at Wuhan Tongji Hospital in China uses Infervision's CT software to detect unusual lung formations (https://www.bioworld.com/)

Recent advances in Medical AI

Lung nodule detection

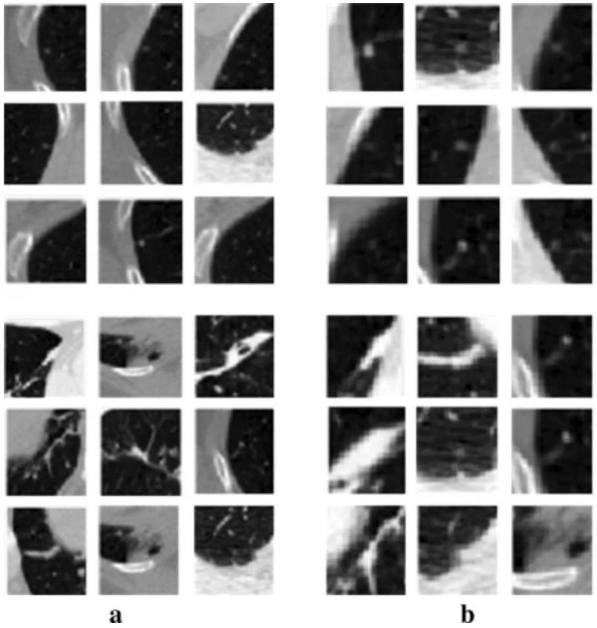


Examples of the suspected lesions and non-nodules identified in the LIDC/IDRI dataset. **a** Nodules (3 mm ≤ diameter < 30 mm); **b** micro-nodules (diameter < 3 mm); **c** non-nodules (3 mm ≤ diameter).

Patrice Monkam et al. "CNN models discriminating between pulmonary micro-nodules and non-nodules from CT images", *BioMedical Engineering OnLine* volume 17, Article number: 96 (2018)

Recent advances in Medical AI

Lung nodule detection



The extracted patches of micro-nodules (**a**) and non-nodules (**b**).

Source: Patrice Monkam et al. "CNN models discriminating between pulmonary micro-nodules and non-nodules from CT images", *BioMedical Engineering OnLine* volume 17, Article number: 96 (2018).

Recent advances in Medical AI

Lung nodule detection

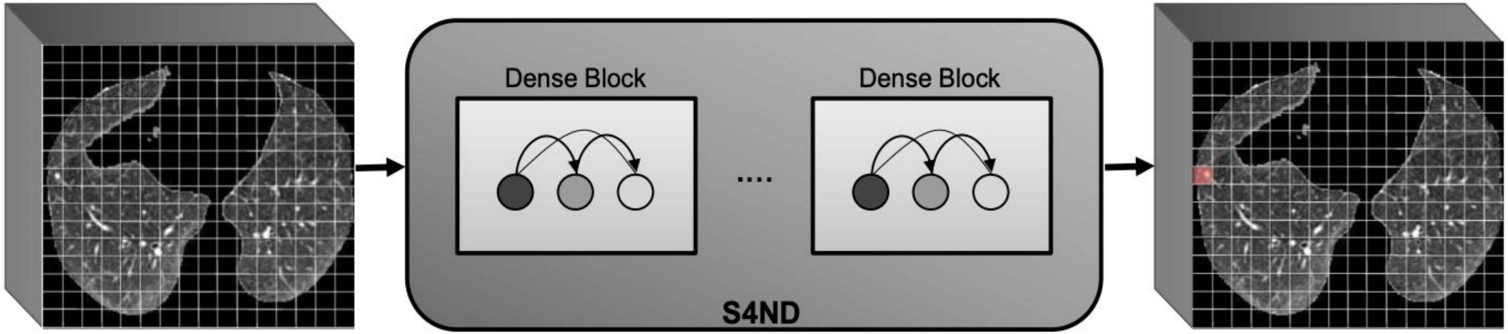
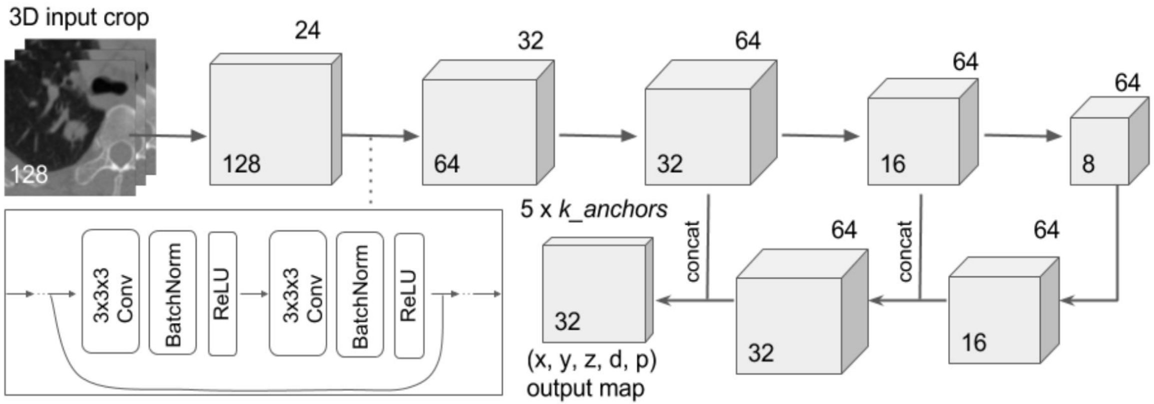


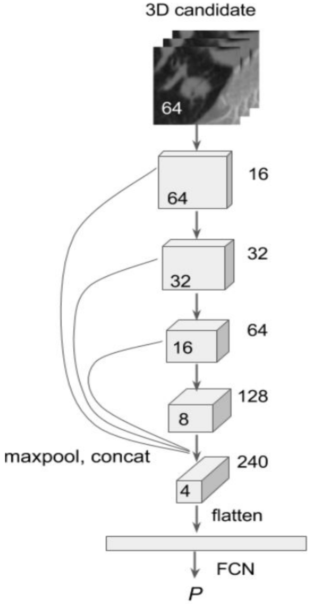
Fig. 1. Our framework, named S4ND, models nodule detection as a cell-wise classification of the input volume. The input volume is divided by a $16 \times 16 \times 8$ grid and is passed through a newly designed $3D$ dense CNN. The output is a probability map indicating the presence of a nodule in each cell.

Tang, Hao, Daniel R. Kim, and Xiaohui Xie. "Automated pulmonary nodule detection using 3D deep convolutional neural networks." *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE, 2018.

Recent advances in Medical AI

Lung nodule detection





This method roughly follows two stages: (1) candidate screening using a 3D Faster R-CNN, and (2) subsequent false positive reduction using 3D D-CNN classifiers. The purpose of the Faster R-CNN in (1) is to identify nodule candidates while preserving high sensitivity, whereas the classifiers in (2) finely discriminate between true nodules and false positives.

Tang, Hao, Daniel R. Kim, and Xiaohui Xie. "Automated pulmonary nodule detection using 3D deep convolutional neural networks." *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE, 2018.

Lung nodule detection

State-of-the-art methods for lung nodule detection

- Wentao Zhu, Chaochun Liu, Wei Fan, and Xiaohui Xie. Deeplung: Deep 3D dual path nets for automated pulmonary nodule detection and classification. In *2018 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pages 673–681. IEEE, 2018.

- Yuemeng Li, Hangfan Liu, and Yong Fan. DeepSEED: 3D squeeze-and-excitation encoder-decoder convnets for pulmonary nodule detection. *CoRR*, abs/1904.03501, 2019.

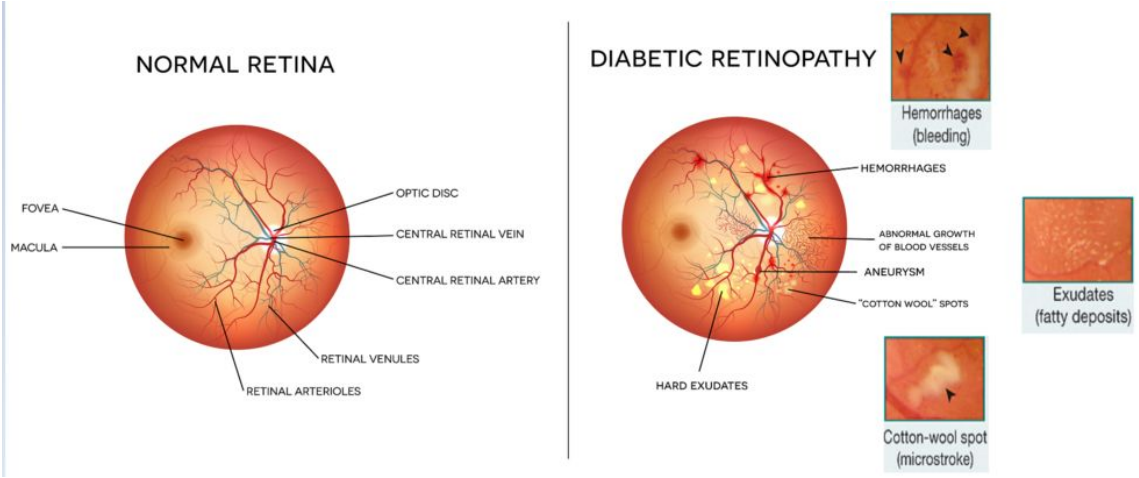
- Naji Khosravan and Ulas Bagci. S4ND: Single-shot singlescale lung nodule detection. In I*nternational Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 794–802. Springer, 2018.

- Jingya Liu, Liangliang Cao, Oguz Akin, and Yingli Tian. 3DFPN-HS2 : 3D feature pyramid network based high sensitivity and specificity pulmonary nodule detection. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 513–521. Springer, 2019.

Recent advances in Medical AI

Diabetic retinopathy Detection (bệnh võng mạc tiểu đường)

- Diabetic retinopathy (DR) is the leading cause of blindness in the working-age population of the developed world. It is estimated to affect over 93 million people.
- DR detection is a manual and time-consuming process that requires a trained clinician to examine and evaluate digital color retinal photographs.
- The need for a comprehensive and automated method of DR screening has long been recognized



Sourced from https://devmesh.intel.com/

Recent advances in Medical AI

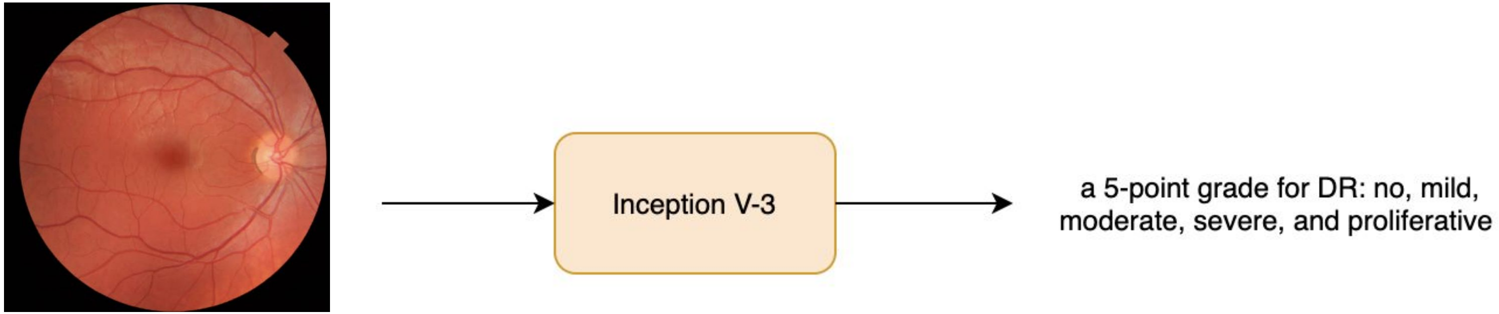
Diabetic retinopathy Detection (bệnh võng mạc tiểu đường)

Google used AI to screen for diabetic retinopathy in India (https://www.docwirenews.com/).

Recent advances in Medical AI

Diabetic retinopathy Detection (bệnh võng mạc tiểu đường)

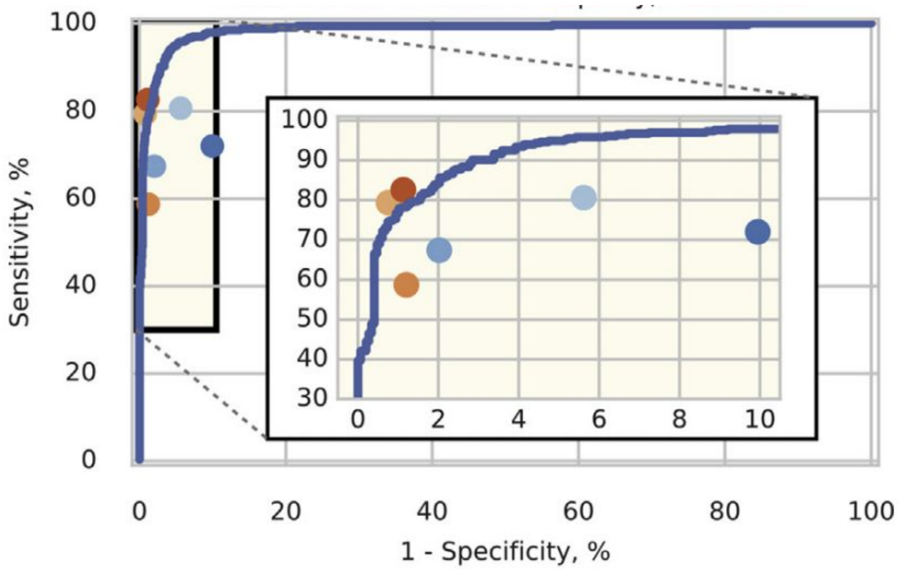
	Development		Clinical Validation
	Train	*Tune*	*EyePACS-2*
Images (No.)	1 665 151	3737	1958
Patient Demographics			
Unique individuals (No.)	238 610	2643	999
Age (average ± SD)	53.5±11.6	54.3±11.1	54.9±10.9
Female/total patients where gender was known	140 183/230 556 (60.8%)	1101/1767 (62.3%)	603/997 (60.5%)
Image Quality Distribution			
Fully gradable/total images where image quality was assessed	1 343 726/1529 771 (87.8%)	3547/3737 (94.9%)	1813/1958 (92.6%)



Jonathan Krause et al. “Grader Variability and the Importance of Reference Standards for Evaluating Machine Learning Models for Diabetic Retinopathy” - *Ophthalmology* 2018.

Recent advances in Medical AI

Diabetic retinopathy Detection (bệnh võng mạc tiểu đường)



Jonathan Krause et al. “Grader Variability and the Importance of Reference Standards for Evaluating Machine Learning Models for Diabetic Retinopathy” - *Ophthalmology* 2018.

Recent advances in Medical AI

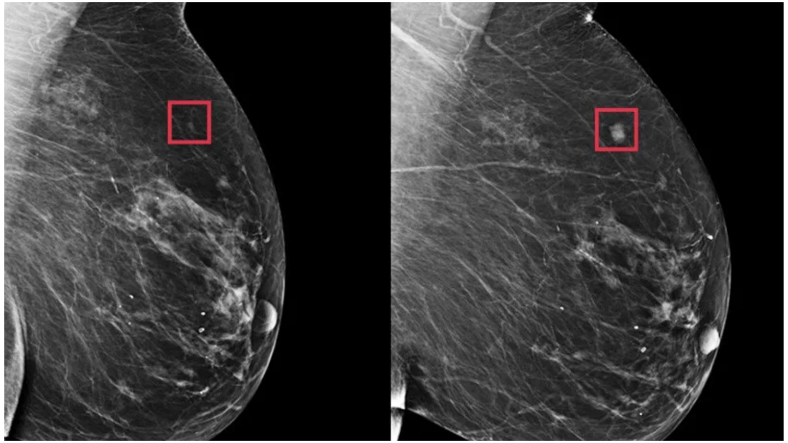
Breast cancer detection

- Mammography is the current standard for breast cancer screening
- Mammography have helped reduce the mortality rate by 39 percent since 1989

This MIT AI Predicts Breast Cancer Risk Up to 5 Years in Advance

MIT CSAIL scientists partnered with Massachusetts General Hospital to develop a deep-learning model that was trained on 90,000 full-resolution mammogram scans from 60,000 patients who were scanned over the course of several years with various outcomes.

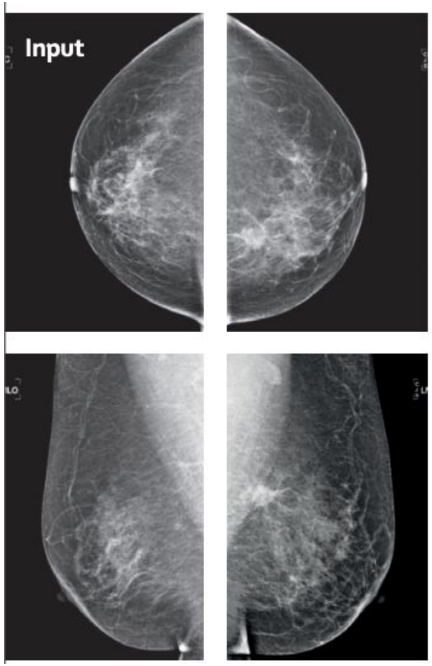
By Ben Dickson May 23, 2019, 9:44 p.m.

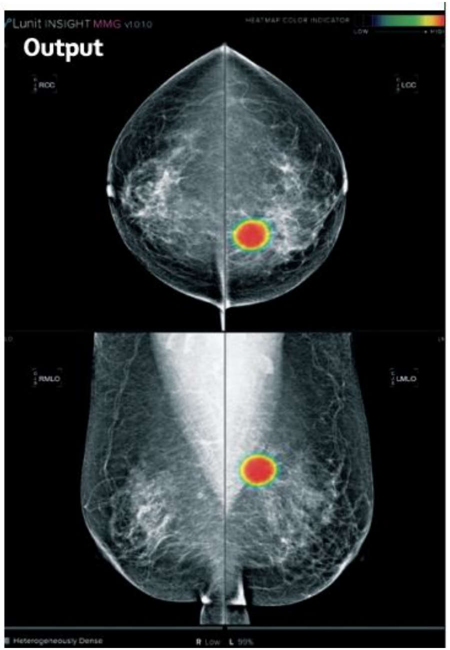


From https://news.mit.edu/, May 7, 2019

Recent advances in Medical AI

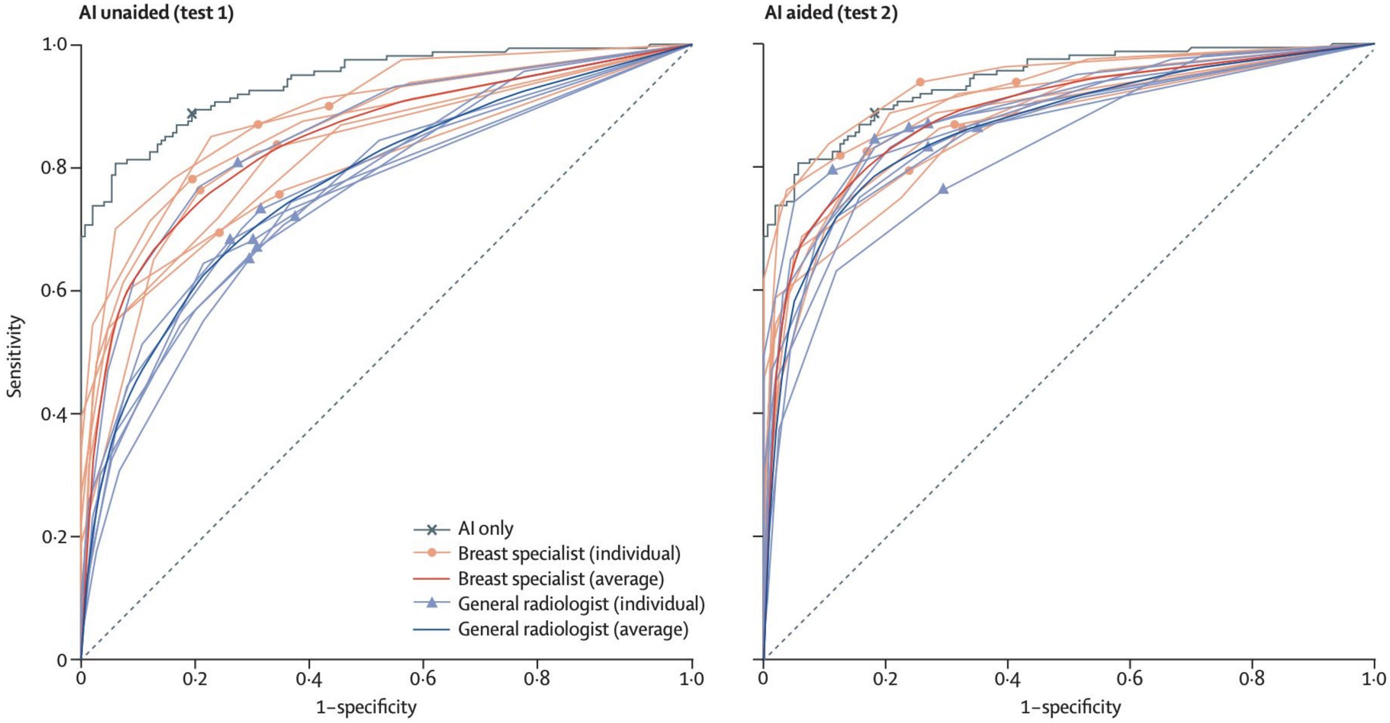
Breast cancer detection aimed to develop an artificial intelligence (AI) algorithm for diagnosis of breast cancer in mammography, and explore whether it could benefit radiologists by improving accuracy of diagnosis (Kim *et al.* , Lancet, 2018).





Category	Category1	Management	Likelihood of Cancer
0- Assessment	Incomplete Assessment	Additional imaging required	Not applicable yet
1	Negative	Routine annual screening	No cancer detected
2	Benign	Routine annual screening	0%
3	Probably Benign	Follow-up scan after 6 months or earlier, as advised by your doctor	0% to 2%
4	Probably Malign	Breast tissue biopsy recommended by the doctor	4A - 2% to 10% 4B - 10% to 50% 4C - 50% to 95%
5	Malignant	Biopsy to be done essentially	>95%
6	Biopsy- Proven Malignancy	Further treatment evaluation is done by the oncologist	Cancer already present

Recent advances in Medical AI



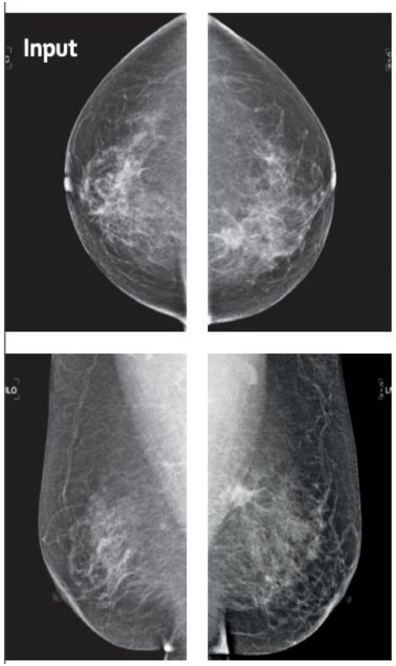
ROC analysis for AI-unaided and AI-aided diagnosis. Kim, Hyo-Eun, et al. "Changes in cancer detection and false-positive recall in mammography using artificial intelligence: a retrospective, multireader study." *The Lancet Digital Health* 2.3 (2020): e138-e148.

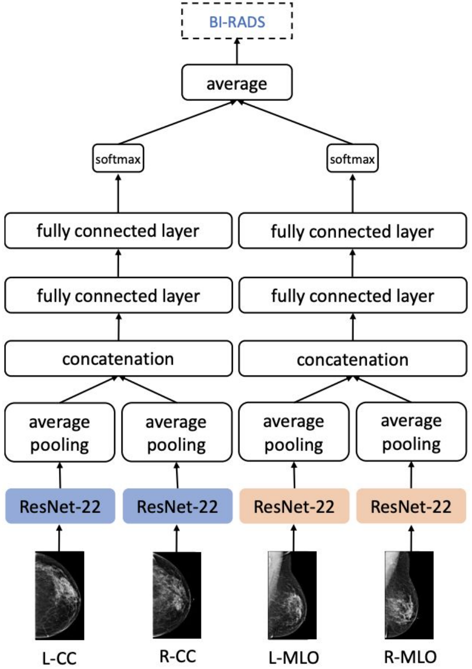
Multi-view approach for breast cancer detection

Key points:

- Light-weight CNNs for handle high-resolution mammo images
- Multi-view fusion for learning abnormality features

Wu, Nan, et al. "Deep neural networks improve radiologists' performance in breast cancer screening." *IEEE transactions on medical imaging* 39.4 (2019): 1184-1194.





Key challenges in Medical AI

- Lack of annotated, benchmark medical imaging dataset
- Noisy labels
- Domain shift problem
- Explainable AI
- Obstacles to clinical translation

Key challenges in Medical AI

VINBIGDATA

Lack of annotated, benchmark medical imaging dataset

Table 1. An overview of existing public datasets for CXR interpretation.

Dataset	Release year	# findings	# samples	Image-level labels	Local labels
JSRT[14]	2000	1	247$^{(\triangleleft,\star)}$	Available	Available
MC[16]	2014	1	138$^{(\triangleleft,\star)}$	Available	N/A
SH[16]	2014	1	662$^{(\triangleleft,\star)}$	Available	N/A
Indiana[15]	2016	10	8,121$^{(\triangleleft,\star)}$	Available	N/A
ChestX-ray8[10]	2017	8	108,948$^{(\bullet)}$	Available	Available$^{(\dagger)}$
ChestX-ray14[10]	2017	14	112,120$^{(\bullet)}$	Available	N/A
CheXpert[3]	2019	14	224,316$^{(\bullet)}$	Available	N/A
Padchest[11]	2019	193	160,868$^{(\bullet,\star)}$	Available	N/A$^{(\dagger\dagger)}$
MIMIC-CXR[12]	2019	14	377,110$^{(\bullet)}$	Available	N/A
VinDr-CXR (ours)	2020	28	18,000$^{(\star)}$	Available	Available

$^{(\bullet)}$ Labeled by an NLP algorithm. $^{(\star)}$ Labeled by radiologists. $^{(\triangleleft)}$ Moderate-size datasets that are not applicable for training deep learning models. $^{(\dagger)}$ A portion of the dataset (983 images) is provided with hand-labeled bounding boxes. $^{(\dagger\dagger)}$ 27% of the dataset was manually annotated with encoded anatomical regions of the findings.

Nguyen, Ha Q., *et al.* "VinDr-CXR: An open dataset of chest X-rays with radiologist's annotations." *arXiv preprint arXiv:2012.15029* (2020).

Key challenges in Medical AI

Lack of annotated, benchmark medical imaging dataset

It is costly and time-consuming to build such datasets due to several constraints:

(1) Medical data are hard to retrieve from hospitals or medical centers;

(2) Physician's time is precious;

(3) The annotation of medical images requires a consensus of several expert readers to overcome human bias;

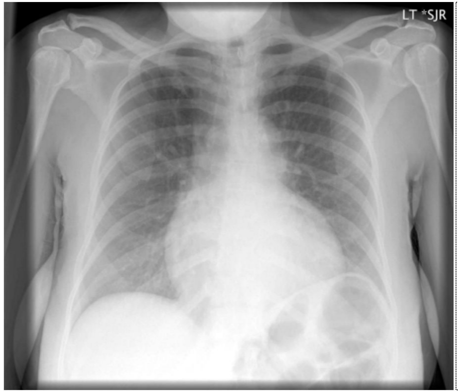
(4) It lacks an efficient labeling framework to manage and annotate large-scale medical datasets.

Nguyen, Ha Q., *et al.* "*VinDr-CXR: An open dataset of chest X-rays with radiologist's annotations*." *arXiv preprint arXiv:2012.15029* (2020).

Key challenges in Medical AI

Learning with noisy labels and limited data

Errors or uncertainty in automatic labeling tool



Findings:
The cardiac silhouette is enlarged and has a globular appearance. Mild bibasilar dependent atelectasis. No pneumothorax or large pleural effusion. No acute bone abnormality.

Impression:
Cardiomegaly with globular appearance of the cardiac silhouette. Considerations would include pericardial effusion or dilated cardiomyopathy.

An example of chest X-ray image along with its report. In the report, the Findings section records detailed descriptions for normal and abnormal findings; the Impression section provides a diagnostic conclusion. The underlined sentence is an abnormal finding (https://www.aclweb.org/anthology/P19-1657.pdf).

1. *unremarkable* cardiomediastinal silhouette

2. diffuse reticular pattern, which can be seen with an atypical infection **or** chronic fibrotic change. *no* focal consolidation.

3. *no* pleural effusion or pneumothorax

4. mild degenerative changes in the lumbar spine and old right rib fractures.

Observation	**Labeler Output**
No Finding	
Enlarged Cardiom.	0
Cardiomegaly	
Lung Opacity	1
Lung Lesion	
Edema	
Consolidation	0
Pneumonia	u
Atelectasis	
Pneumothorax	0
Pleural Effusion	0
Pleural Other	
Fracture	1
Support Devices	

Rule-based CheXpert labeler (from Chexpert's paper)

Key challenges in Medical AI

Learning with noisy labels and limited data

Uncertainty approaches

CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison

Jeremy Irvin, Pranav Rajpurkar, Michael Ko, Yifan Yu, Silviana Ciurea-Ilcus, Chris Chute, Henrik Marklund, Behzad Haghgoo, Robyn Ball, Katie Shpanskaya, Jayne Seekins, David A. Mong, Safwan S. Halabi, Jesse K. Sandberg, Ricky Jones, David B. Larson, Curtis P. Langlotz, Bhavik N. Patel, Matthew P. Lungren, Andrew Y. Ng

Large, labeled datasets have driven deep learning methods to achieve expert-level performance on a variety of medical imaging tasks. We present CheXpert, a large dataset that contains 224,316 chest radiographs of 65,240 patients. We design a labeler to automatically detect the presence of 14 observations in radiology reports, capturing uncertainties inherent in radiograph interpretation. We investigate different approaches to using the uncertainty labels for training convolutional neural networks that output the probability of these observations given the available frontal and lateral radiographs. On a validation set of 200 chest radiographic studies which were manually annotated by 3 board-certified radiologists, we find that different uncertainty approaches are useful for different pathologies. We then evaluate our best model on a test set composed of 500 chest radiographic studies annotated by a consensus of 5 board-certified radiologists, and compare the performance of our model to that of 3 additional radiologists in the detection of 5 selected pathologies. On Cardiomegaly, Edema, and Pleural Effusion, the model ROC and PR curves lie above all 3 radiologist operating points. We release the dataset to the public as a standard benchmark to evaluate performance of chest radiograph interpretation models.
The dataset is freely available at this https URL .

Key challenges in Medical AI

Learning with noisy labels and limited data

Uncertainty approaches

[Submitted on 15 Nov 2019 (v1), last revised 12 Jun 2020 (this version, v3)]

Interpreting chest X-rays via CNNs that exploit hierarchical disease dependencies and uncertainty labels

Hieu H. Pham, Tung T. Le, Dat Q. Tran, Dat T. Ngo, Ha Q. Nguyen

Chest radiography is one of the most common types of diagnostic radiology exams, which is critical for screening and diagnosis of many different thoracic diseases. Specialized algorithms have been developed to detect several specific pathologies such as lung nodule or lung cancer. However, accurately detecting the presence of multiple diseases from chest X-rays (CXRs) is still a challenging task. This paper presents a supervised multi-label classification framework based on deep convolutional neural networks (CNNs) for predicting the risk of 14 common thoracic diseases. We tackle this problem by training state-of-the-art CNNs that exploit dependencies among abnormality labels. We also propose to use the label smoothing technique for a better handling of uncertain samples, which occupy a significant portion of almost every CXR dataset. Our model is trained on over 200,000 CXRs of the recently released CheXpert dataset and achieves a mean area under the curve (AUC) of 0.940 in predicting 5 selected pathologies from the validation set. This is the highest AUC score yet reported to date. The proposed method is also evaluated on the independent test set of the CheXpert competition, which is composed of 500 CXR studies annotated by a panel of 5 experienced radiologists. The performance is on average better than 2.6 out of 3 other individual radiologists with a mean AUC of 0.930, which ranks first on the CheXpert leaderboard at the time of writing this paper.

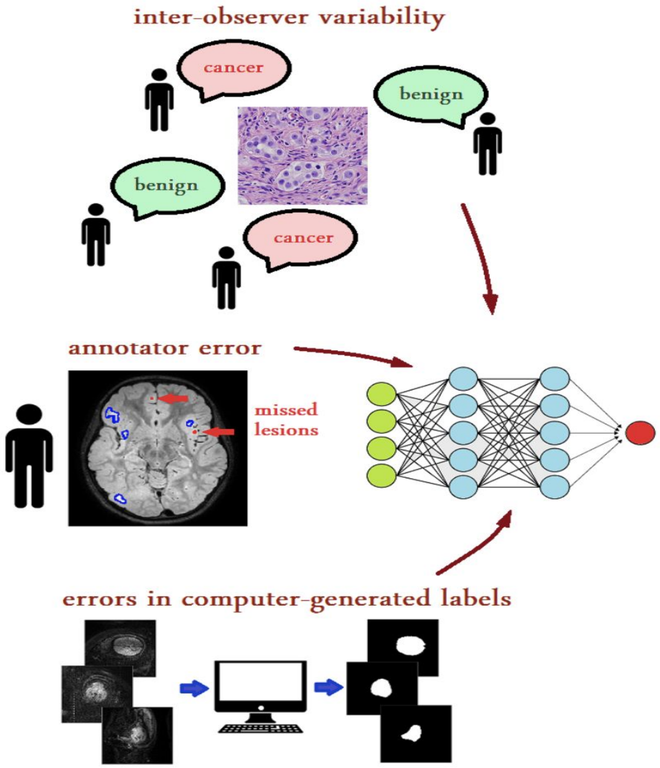
Comments: This is a pre-print of our paper that was accepted by Neurocomputing - Its shorter version has been accepted by Medical Imaging with Deep Learning conference (MIDL 2020)
Subjects: **Image and Video Processing (eess.IV)**; Computer Vision and Pattern Recognition (cs.CV)
Cite as: arXiv:1911.06475 **[eess.IV]**
(or arXiv:1911.06475v3 **[eess.IV]** for this version)

Key challenges in Medical AI

Learning with noisy labels and limited data

Inter-observer variability and annotation errors

- The major sources of label noise include inter-observer variability, human annotator's error, and errors in computer-generated labels.
- The significance of label noise in such datasets is likely to increase as larger datasets are prepared for deep learning.

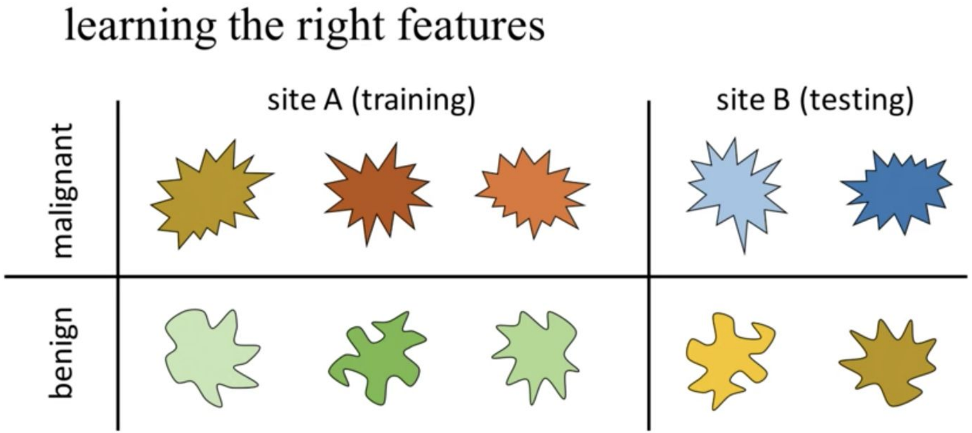


More details from Karimi *et al.* at https://arxiv.org/pdf/1912.02911.pdf

Key challenges in Medical AI

Domain shift problem

Machine learning has been widely used in medical image analysis, and typically assume that the training dataset (source/reference domain) and test dataset (target domain) share the same data distribution

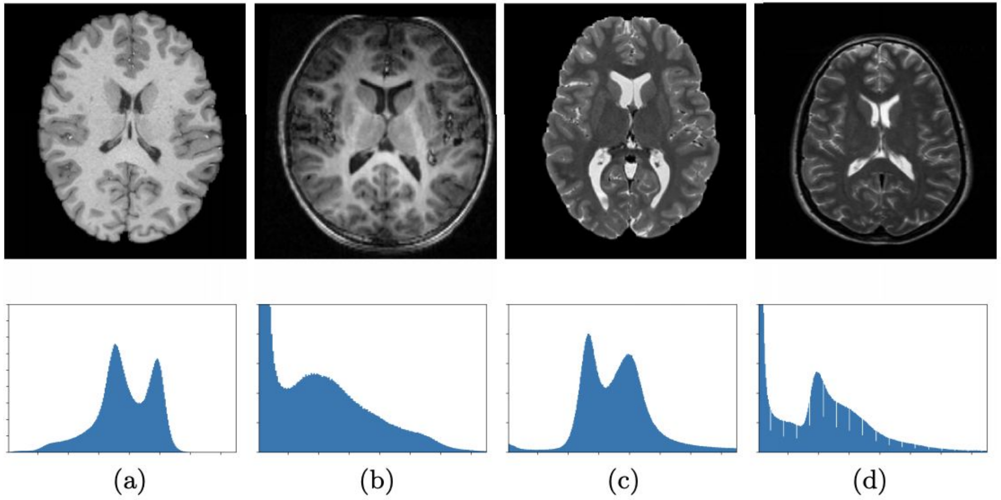


However, this assumption is too strong and may not hold in real-world practice (figure was reused from Ben Glocker, Imperial College London, 2019)

Key challenges in Medical AI

Domain shift problem

Medical imaging is generated from different scanners, scanner parameters, and subject cohorts



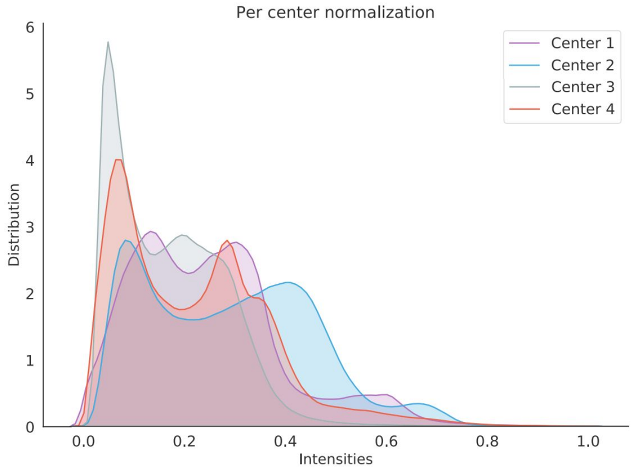
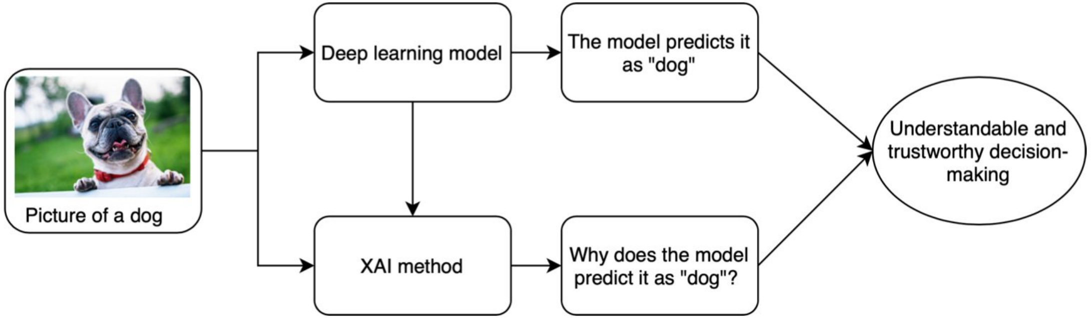


Image slices (top) and corresponding intensity distribution (bottom) of normalized T1-weighted (a, b) and T2-weighted (c, d) MRIs from different scanners (https://arxiv.org/pdf/2102.09508.pdf). Intensity distribution of MRI axial-slice pixels from four different datasets (i.e., UCL, Montreal, Zurich, and Vanderbilt) that collected for gray matter segmentation.

Key challenges in Medical AI

Explainable AI

Interpretability (the degree to which human can understand the cause of a decision) is the key enabler in medical AI.

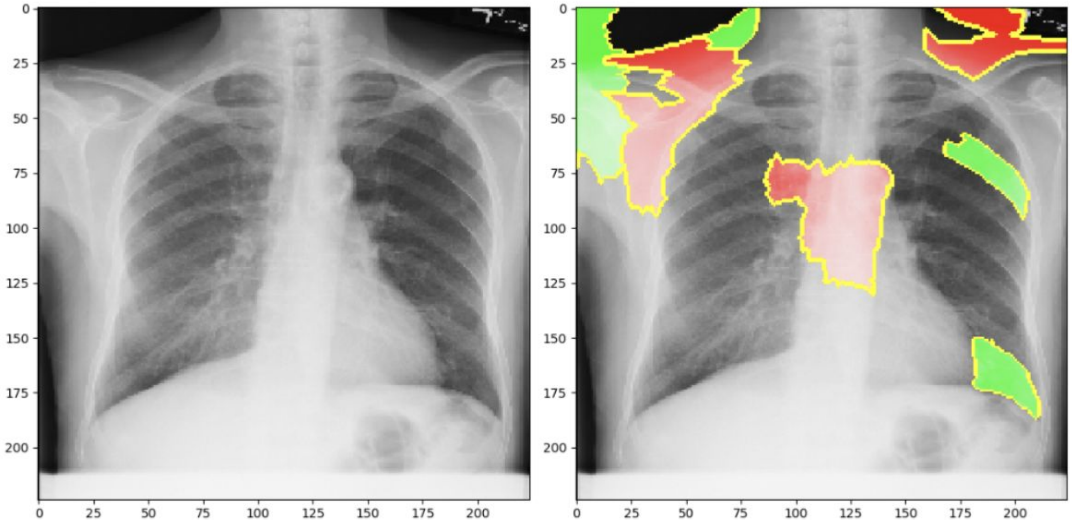


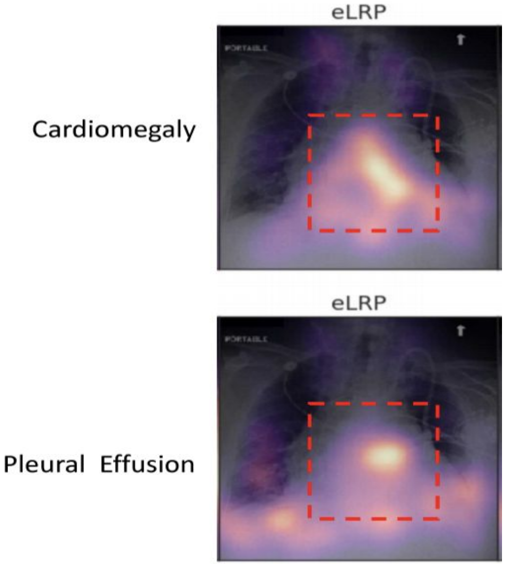
Singh et al., “Explainable Deep Learning Models in Medical Image Analysis” - *Deep Learning in Medical Image Analysis,* 2020

Key challenges in Medical AI

Explainable AI

Produce heatmaps [GradCAM, GBP, Class Activation Maps - CAM] for verifying the features learned by the proposed deep learning model.





See more details at https://arxiv.org/pdf/2005.13799.pdf

Key challenges in Medical AI

VINBIGDATA

Obstacles to clinical translation

Robustness: Data mismatch, population shift, acquisition shift [3,5]

Availability: Missingness [1,3,4], privacy concerns [3,5,6], unstructured records [1,4,6], inconsistent information encoding [1,4]

Reliability: Data entry errors, bugs, inaccuracy [1,4], label uncertainty [3,5,6]

[1] S Hoffman & A Podgurski, Am J Law & Med 39, 2013

[2] JW Swanson & JK Ibrahim, PHLR: Th & Meth 2013

[3] M Ghassemi et al., Lancet Dig Health 1, 2019

[4] ND Shah et al., JAMA 320, 2018

[5] LM Prevedello et al., Radiology: AI 1, 2019

[6] CP Langlotz et al., Radiology 291, 2019

Key challenges in Medical AI

VINBIGDATA

Clinical trial for interventions involving AI.

- Inclusion/exclusion criteria at subject & record levels
- Acquisition, selection, and pre-processing of input data
- Handling of noisy/missing data

nature medicine

CONSENSUS STATEMENT

https://doi.org/10.1038/s41591-020-1037-7

Check for updates

OPEN

Guidelines for clinical trial protocols for interventions involving artificial intelligence: the SPIRIT-AI extension

Samantha Cruz Rivera[1,2,3], Xiaoxuan Liu[3,4,5,6,7], An-Wen Chan[8], Alastair K. Denniston[1,3,4,5,6,9] ✉, Melanie J. Calvert[1,2,3,6,10,11,12], The SPIRIT-AI and CONSORT-AI Working Group*, SPIRIT-AI and CONSORT-AI Steering Group and SPIRIT-AI and CONSORT-AI Consensus Group

CONSENSUS STATEMENT

https://doi.org/10.1038/s41591-020-1034-x

nature medicine

Check for updates

OPEN

Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension

Xiaoxuan Liu[1,2,3,4,5], Samantha Cruz Rivera[5,6,7], David Moher[8,9], Melanie J. Calvert[4,5,6,7,10,11,12], Alastair K. Denniston[2,3,4,5,6,13] ✉ and The SPIRIT-AI and CONSORT-AI Working Group*

Medical AI: An experience from VinBigdata

Medical AI at VinBigdata

VINBIGDATA

VinDr Project (https://vindr.ai/)

A comprehensive solution for medical image analysis that integrates Artificial Intelligence (AI) into a Picture Archiving and Communication System (PACS) to assist radiologists in making fast and precise diagnoses.

"They should stop training radiologists now."
Geoffrey Hinton (godfather of deep learning) in 2017

"To the question, will AI replace radiologists, I say the answer is no…"

"… but radiologists who do AI will replace radiologists who don't."
Curtis Langlotz in 2017


RSNA News

Machine Learning Plays Central Role at RSNA 2017

BY MIKE BASSETT

November 1, 2017

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Langlotz

Machine Learning (ML) and the role it will play in the future of radiology will be central to a broad scope of programming at RSNA 2017.

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Aims of the project

1 - Building large-scale datasets of medical images for multiple imaging modalities (X-ray, CT, MRI) and highly-demanding diseases in Vietnam.

2 - Develop and evaluate AI-based approaches for a wide range of diagnostic application and pushing the frontier of research in medical image analysis

3 - Publish benchmark datasets and papers on top-tier conferences and journals.

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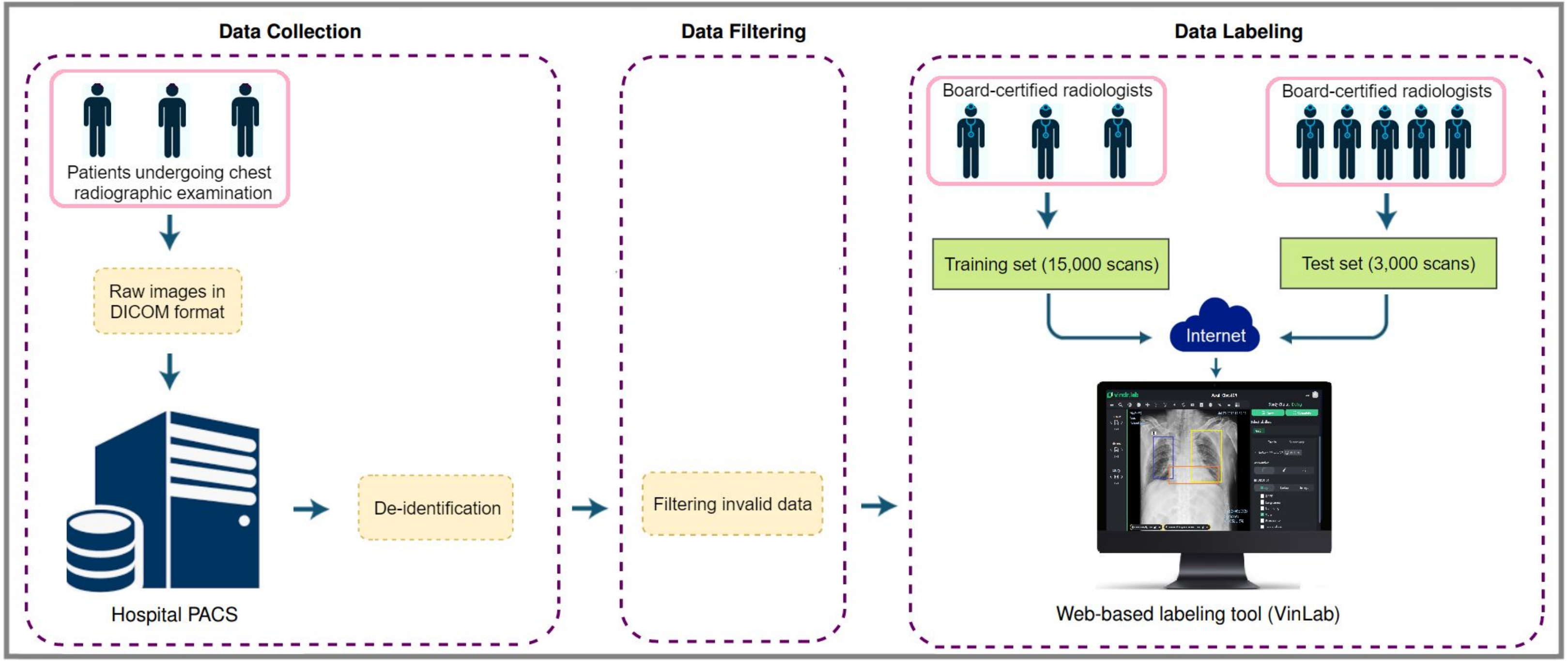
VINBIGDATA

Data collection



Nguyen, Ha Q., *et al.* "VinDr-CXR: An open dataset of chest X-rays with radiologist's annotations." *arXiv preprint arXiv:2012.15029* (2020).

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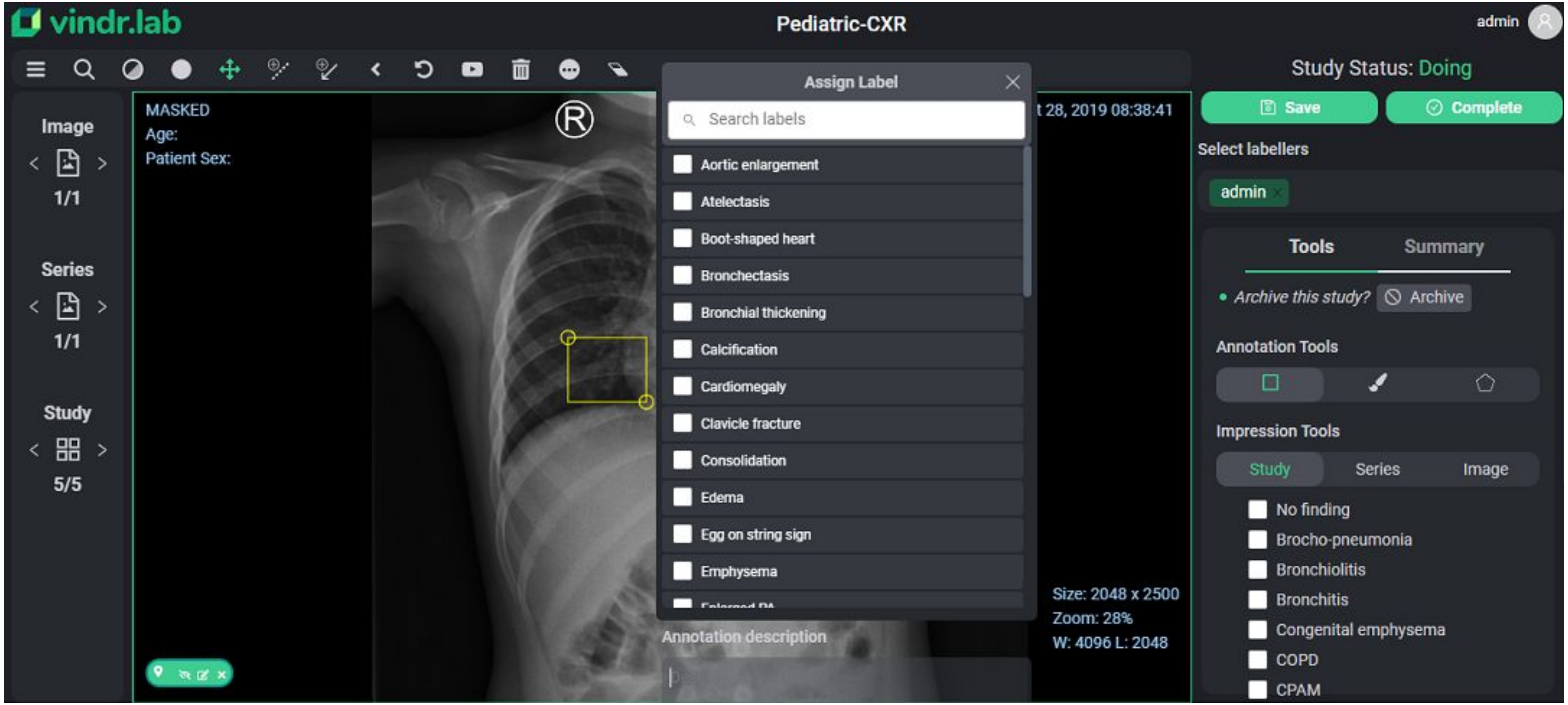
Developing VinDr Lab (https://vindr.ai/vindr-lab) for data annotation



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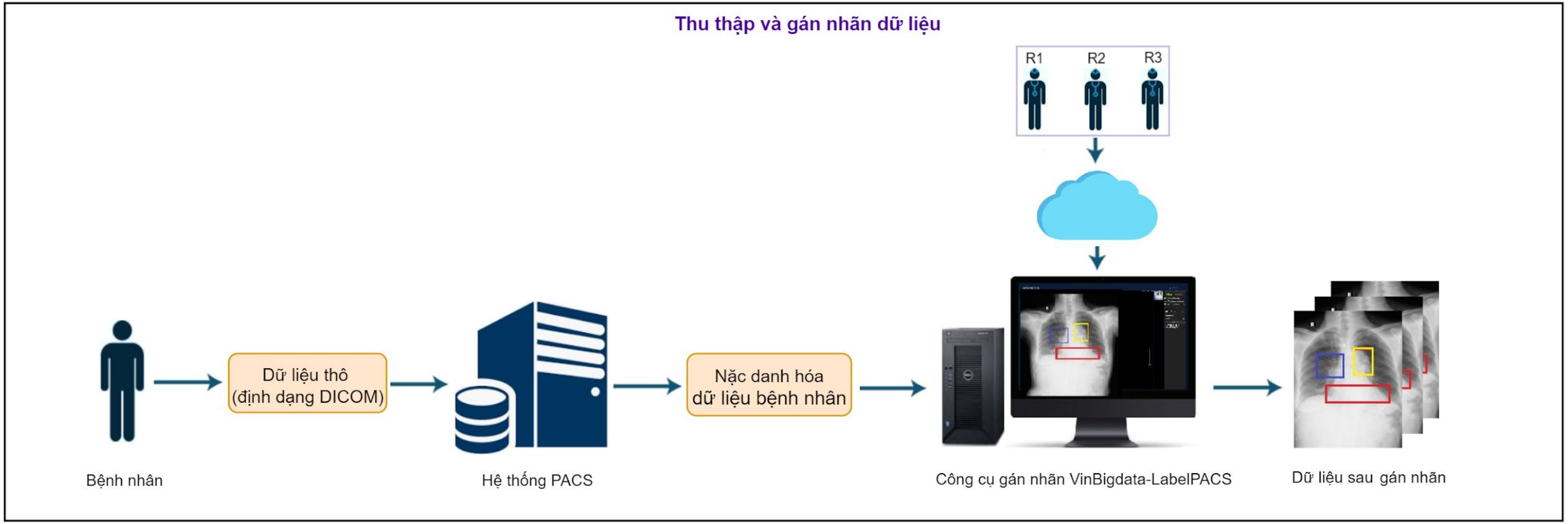
Data annotation



Nguyen, Ha Q., *et al.* "VinDr-CXR: An open dataset of chest X-rays with radiologist's annotations." *arXiv preprint arXiv:2012.15029* (2020).

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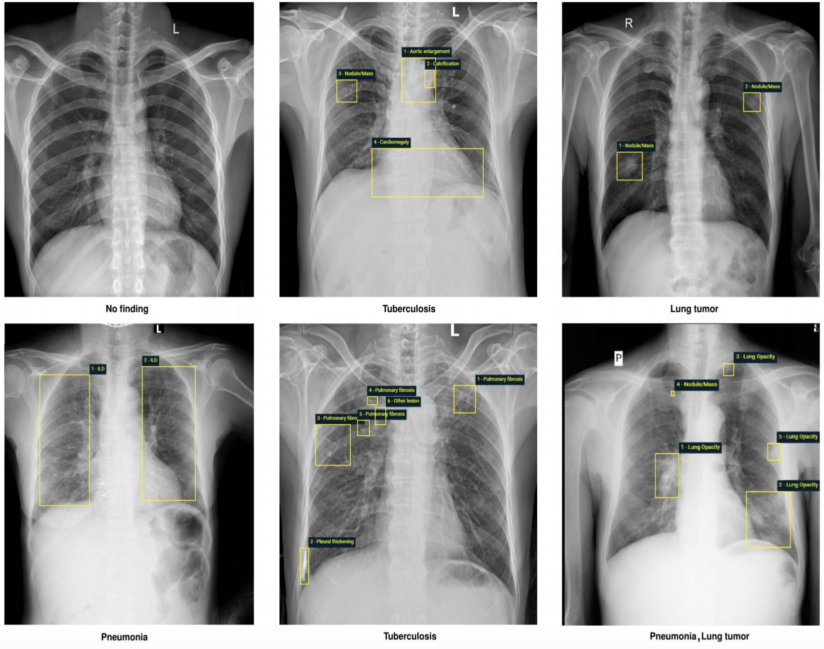
Data collection



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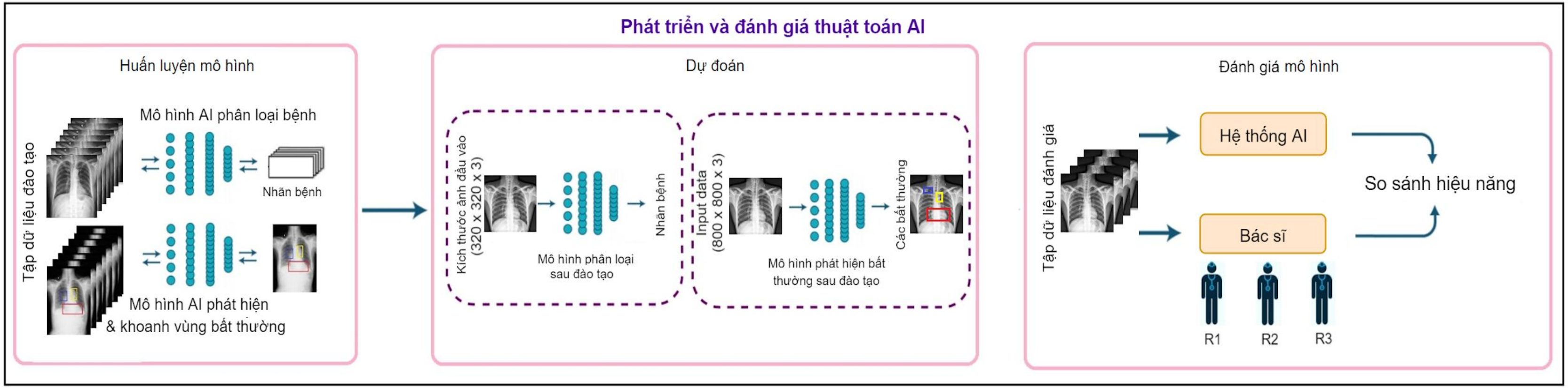
Model development and evaluation



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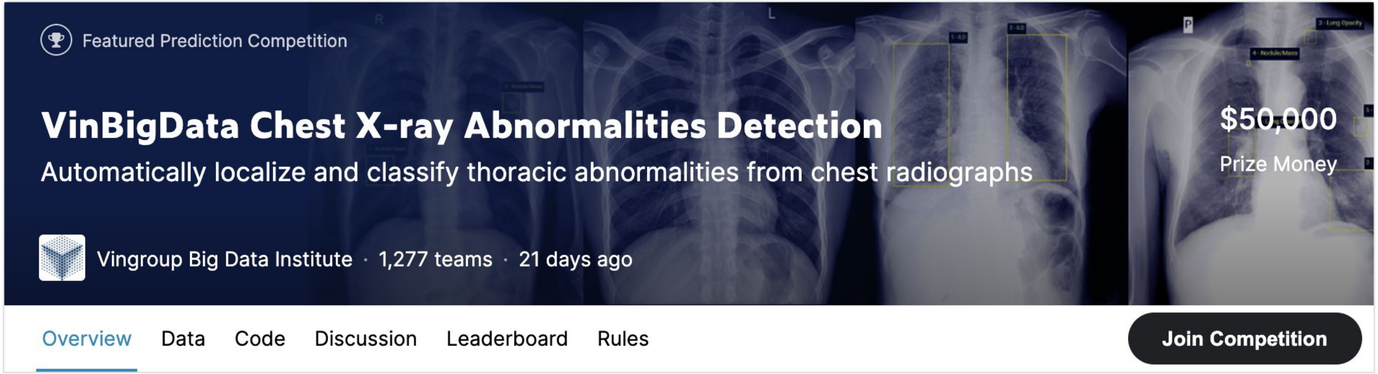
Benchmarking machine learning algorithms

- We actively participated in medical imaging challenges on open platforms (Kaggle, Grand Challenge, workshops, etc.) to build and benchmark AI models
- The models submitted to these challenges generalize well to our own data
- Launch our own challenge on Kaggle



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Integrating AI in clinical workflow

- **PACS**: stores, communicates, and manages DICOM files
- **AI Platform:** receives requests from PACS and splits the tasks to AI workers
- **Viewer**: displays DICOM images and AI results, provides reading tools

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VINBIGDATA

VinDr Study List

VinDr Hiển Thị Trợ Giúp vi

Tất cả | Mới 42 | Đã đọc 1 | Đã duyệt | Bỏ qua | Tải lên

Ngày chụp 30/04/1975 → 17/06/2020 | MG | Bộ phận | Tìm kiếm...

Tên bệnh nhân	Số phiếu	Giới tính	Tuổi	#S/#I	Bộ phận	KT chụp	Ngày chụp	Trạng thái xử lý	Kết quả AI	Kết quả bác sĩ
masked	-	Nữ	48	1/4	BREAST	MG	13/05/2020	Mới	BIRADS 2/3	-
masked	-	Khác	59	1/4	BREAST	MG	13/05/2020	Đã đọc	BIRADS 2/3	BIRADS 5
masked	-	Khác	46	1/4	BREAST	MG	13/05/2020	Mới	BIRADS 2/3	BIRADS 3
masked	-	Nữ	-	5/8	BREAST	MG	07/11/2019	Mới	BIRADS 2/3	-
masked	-	Nữ	0	1/1	BREAST	MG	14/10/2019	Mới	BIRADS 1	-
masked	-	Nữ	68	5/5	BREAST	MG	14/10/2019	Mới	BIRADS 1	-
masked	-	Nữ	43	4/4	BREAST	MG	14/10/2019	Mới	BIRADS 1	-
masked	-	-	61	5/6	BREAST	MG	14/10/2019	Mới	BIRADS 2/3	-
masked	-	-	31	4/4	BREAST	MG	14/10/2019	Mới	BIRADS 1	-
masked	-	Nữ	51	5/5	BREAST	MG	14/10/2019	Mới	BIRADS 1	-
masked	-	Nữ	30	4/4	BREAST	MG	14/10/2019	Mới	BIRADS 4/5	-
masked	-	Nữ	42	4/4	BREAST	MG	11/10/2019	Mới	BIRADS 1	-
masked	-	Nữ	30	4/4	BREAST	MG	11/10/2019	Mới	BIRADS 4/5	-
masked	-	-	54	4/4	BREAST	MG	11/10/2019	Mới	BIRADS 2/3	-
masked	-	Nữ	30	4/4	BREAST	MG	10/10/2019	Mới	BIRADS 2/3	-
masked	-	-	71	4/4	BREAST	MG	10/10/2019	Mới	BIRADS 2/3	-
masked	-	-	27	4/4	BREAST	MG	10/10/2019	Mới	BIRADS 1	-

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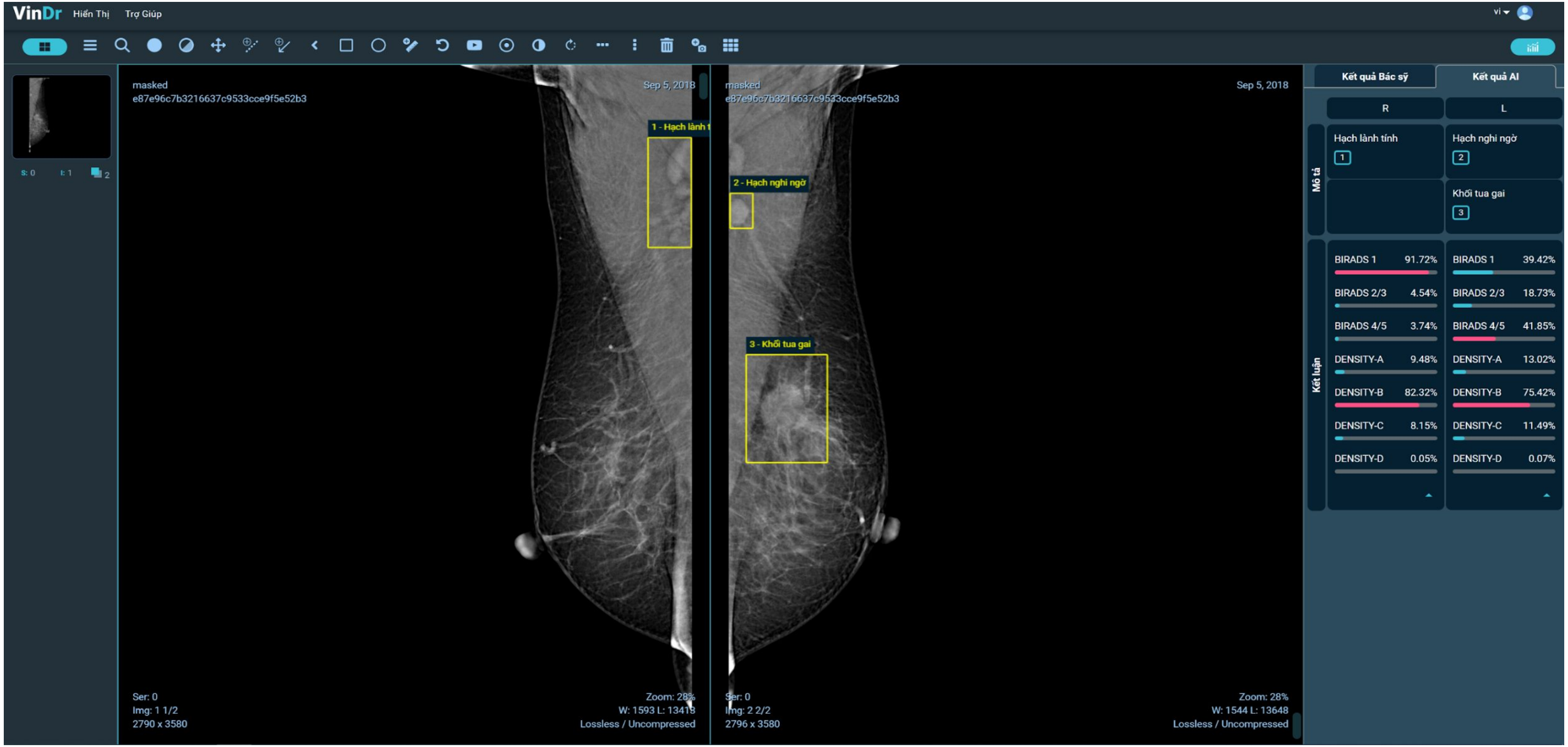
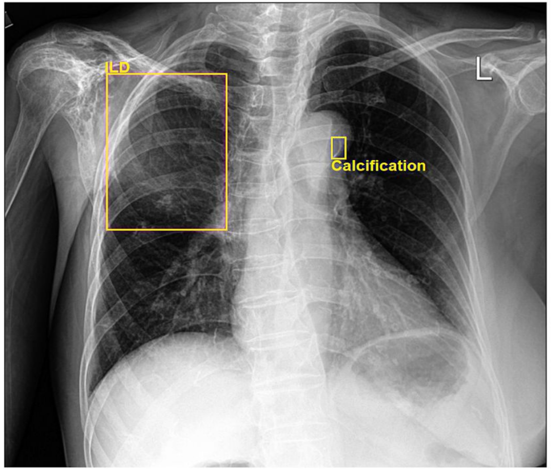
VinDr-Mammo

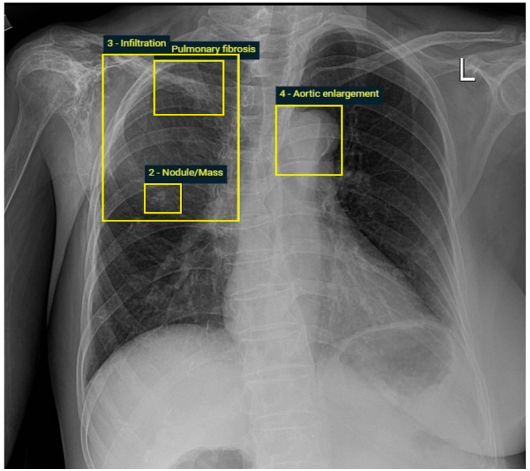


Medical AI at VinBigdata

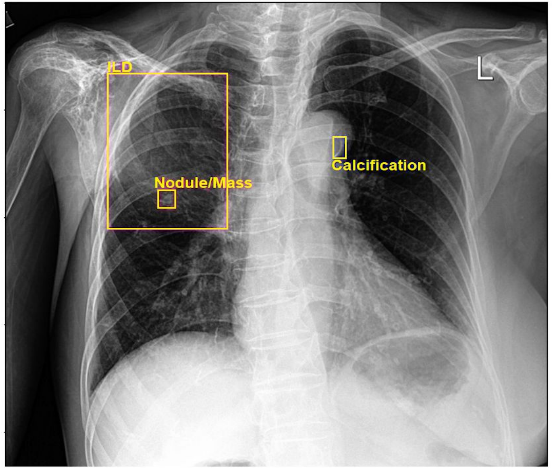
Clinical evaluation: Does AI really help radiologists?



Rad (1st read)



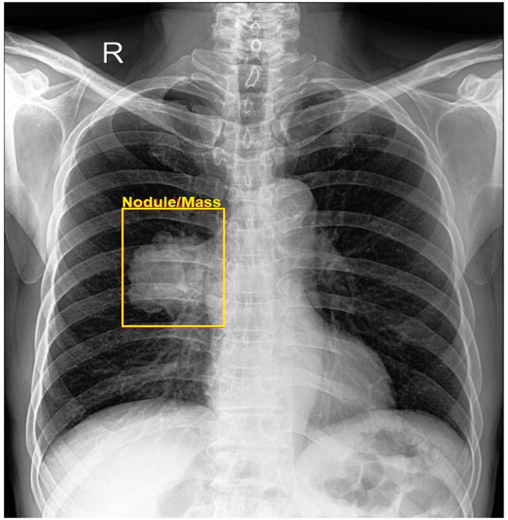
AI



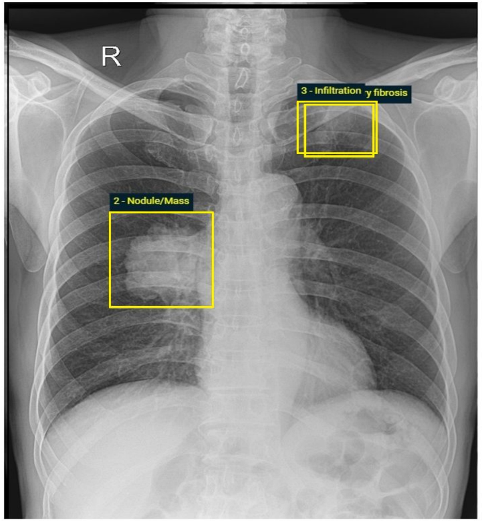
Rad within AI-assisted

Medical AI at VinBigdata

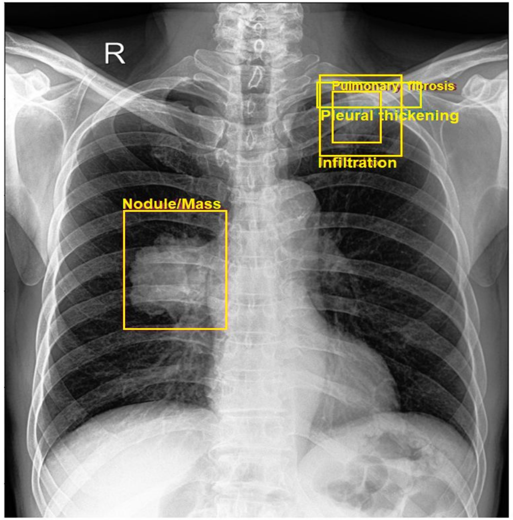
Clinical evaluation: Does AI really help radiologists?



Rad (1st read)



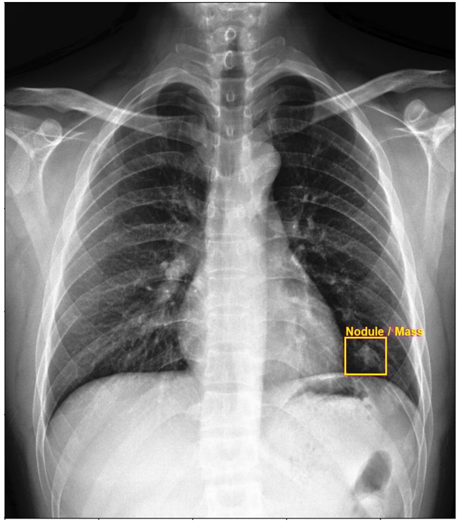
AI



Rad within AI-assisted

Medical AI at VinBigdata

Clinical evaluation: Does AI really help radiologists?



Rad (1st read)

AI

Rad within AI-assisted

Medical AI at VinBigdata

VINBIGDATA

Clinical evaluation at 108 Hospital and HMU: Does AI really help radiologists?

Radiologist	Số ca thay đổi sau khi tham khảo AI	Tỷ lệ
Phạm Minh Chi (108.cxr1)	20/200	10.0%
Lê Duy Dũng (108.cxr2)	13/200	6.5%
Đinh Hoàng Điệp (108.cxr3)	30/200	15.0%

Trung bình: 10.5%

Radiologist	Số ca thay đổi sau khi tham khảo AI	Tỷ lệ
Lê Tuấn Linh (dhy.cxr1)	12/200	6.0%
Đoàn Tiến Lưu (dhy.cxr2)	10/200	5.0%
Nguyễn Ngọc Cương (dhy.cxr3)	7/200	3.5%

Trung bình: 4.8%

Medical AI at VinBigdata

VINBIGDATA

Clinical evaluation at 108 Hospital and HMU: Does AI really help radiologists?

108 Hospital

	108.cxr1	108.cxr2	108.cxr3	AI
108.cxr1	100%			
108.cxr2	91.9%	100%		
108.cxr3	92.1%	92.2%	100%	
AI	90.9%	89.5%	91.1%	100%

Độ đồng thuận trung bình của AI với bác sĩ: **90.5%**

Độ đồng thuận trung bình giữa các bác sĩ với nhau: **92.1%**

HMU

	dhy.cxr1	dhy.cxr2	dhy.cxr3	AI
dhy.cxr1	100%			
dhy.cxr2	90.8%	100%		
dhy.cxr3	88.7%	89.7%	100%	
AI	89%	91.7%	87.7%	100%

Độ đồng thuận trung bình của AI với bác sĩ: **89.5%**

Độ đồng thuận trung bình giữa các bác sĩ với nhau: **89.7%**

Medical AI at VinBigdata

VINBIGDATA

A few remarks

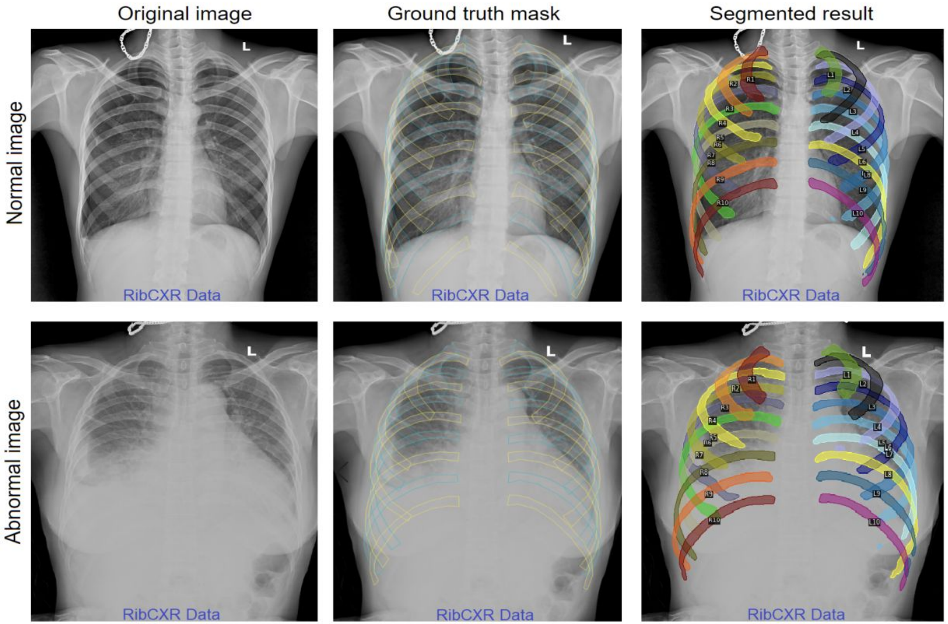
- From experiments, AI does help radiologists in spotting abnormalities
- The difference between AI and a good doctor in reading a **single image** seems to be the same as the difference between the doctors themselves
- The hardest part is to measure the effect of AI in real clinical practice

What's next

- Integrate multi-modal and longitudinal data
- Take into account cheap devices (wearable sensors, smart-phone cameras, mobile devices)

Medical AI at VinBigdata

RibCXR: A Benchmark Dataset for Automatic Segmentation and Labeling of Individual Ribs on Chest X-rays



Hoang Canh Nguyen, Tung Thanh Le, Hieu Pham, Ha Quy Nguyen. "VinDr-RibCXR: A Benchmark Dataset for Automatic Segmentation and Labeling of Individual Ribs on Chest" - PDF: https://openreview.net/pdf?id=oJi6xpSLdsj; *MIDL 2021* (submitted).

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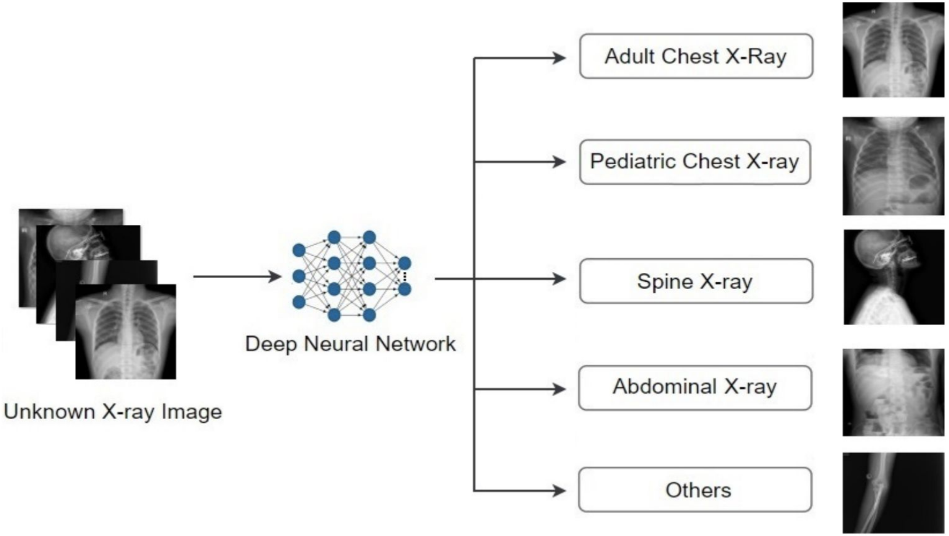
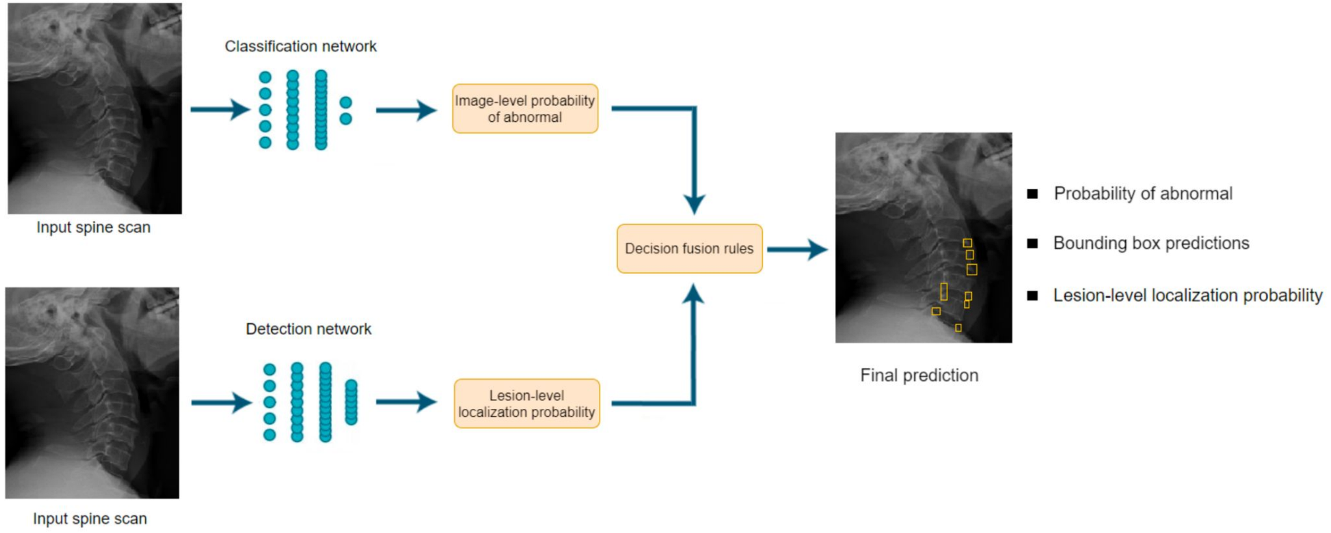
Automatic Classification of Human Body Parts from X-ray Images Using Deep Convolutional Neural



Dung D. Do, Hieu Pham, Ha Quy Nguyen. "Automatic Classification of Human Body Parts from X-ray Images Using Deep Convolutional Neural Networks" - PDF: https://openreview.net/pdf?id=zKBgupz4 ; *MIDL 2021* (submitted).

Development and validation of a deep learning-based framework for spinal lesions detection and classification from radiograph



Hieu Nguyen, Hieu Pham, Ha Quy Nguyen. "Development and validation of a deep learning-based framework for spinal lesions detection and classification from radiographs" - *MICCAI 2021* (submitted)

THANK YOU!

(v.hieuph4@vinbigdata.org)