

6th July 2022

Bringing AI into Radiological Practice

Challenges & Opportunities

Women in Data Science

x





Welcome



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COO, Co-Founder



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X-Ray

Mammography

Ultrasound

MRI

CT

First PACS

1895

1913

1942

1971 1972



X-Ray

1895



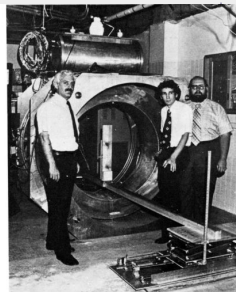
Mammography

1913



Ultrasound

1942

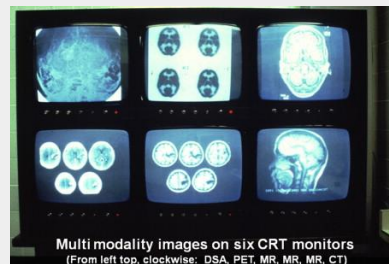


MRI

1971

CT

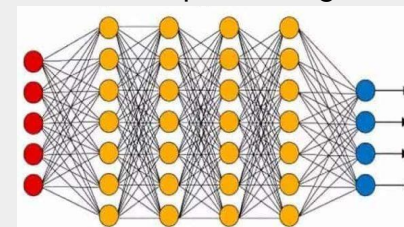
1972



First PACS

2015

Breakthrough of AI with Deep Learning



CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

Pranav Rajpurkar^{*1} Jeremy Irvin^{*1} Kaylie Zhu¹ Brandon Yang¹ Hershel Mehta¹
Tony Duan¹ Daisy Ding¹ Aarti Bagul¹ Robyn L. Ball² Curtis Langlotz³ Katie Shpankaya³
Matthew P. Lungren³ Andrew Y. Ng¹

Abstract

We develop an algorithm that can detect pneumonia from chest X-rays at a level exceeding practicing radiologists. Our algorithm, CheXNet, is a 121-layer convolutional neural network trained on ChestX-ray14, currently the largest publicly available chest X-ray dataset, containing over 100,000 frontal-view X-ray images with 14 diseases. Four practicing academic radiologists annotate a test set, on which we compare the performance of CheXNet to that of radiologists. We find that CheXNet exceeds average radiologist performance on the F1 metric. We extend CheXNet to detect all 14 diseases in ChestX-ray14 and achieve state of the art results on all 14 diseases.

1. Introduction

More than 1 million adults are hospitalized with pneumonia and around 50,000 die from the disease every year in the US alone (CDC, 2017). Chest X-rays are currently the best available method for diagnosing pneumonia (WHO, 2001), playing a crucial role in clinical care (Franquet, 2001) and epidemiological studies (Cherian et al., 2005). However, detecting pneumonia in chest X-rays is a challenging task that relies on the availability of expert radiologists. In this work, we present a model that can automatically detect pneumonia from chest X-rays at a level exceeding practicing radiologists.

^{*}Equal contribution ¹Stanford University Department of Computer Science ²Stanford University Department of Medicine ³Stanford University Department of Radiology. Correspondence to: Pranav Rajpurkar <pranavar@cs.stanford.edu>, Jeremy Irvin <jirvin@cs.stanford.edu>.
Project website at <https://stanfordmlgroup.github.io/projects/chexnet>

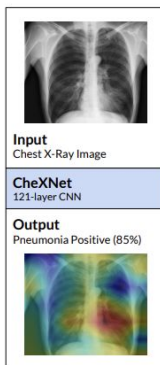


Figure 1. CheXNet is a 121-layer convolutional neural network that takes a chest X-ray image as input, and outputs the probability of a pathology. On this example, CheXNet correctly detects pneumonia and also localizes areas in the image most indicative of the pathology.

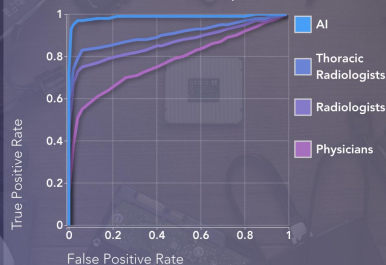
Our model, CheXNet (shown in Figure 1), is a 121-layer convolutional neural network that inputs a chest X-ray image and outputs the probability of pneumonia along with a heatmap localizing the areas of the image most indicative of pneumonia. We train CheXNet on the recently released ChestX-ray14 dataset (Wang et al., 2017), which contains 112,120 frontal-view chest X-ray images individually labeled with up to 14 different thoracic diseases, including pneumonia. We use

	F1 Score (95% CI)
Radiologist 1	0.383 (0.309, 0.453)
Radiologist 2	0.356 (0.282, 0.428)
Radiologist 3	0.365 (0.291, 0.435)
Radiologist 4	0.442 (0.390, 0.492)
Radiologist Avg.	0.387 (0.330, 0.442)
CheXNet	0.435 (0.387, 0.481)

AI vs Doctors: Chest X-Rays


AI was significantly more accurate and precise than radiologists and physicians in diagnosing chest x-rays.

AUC-ROC: Human vs Computer



Chinese AI beats 15 doctors in tumor diagnosis competition





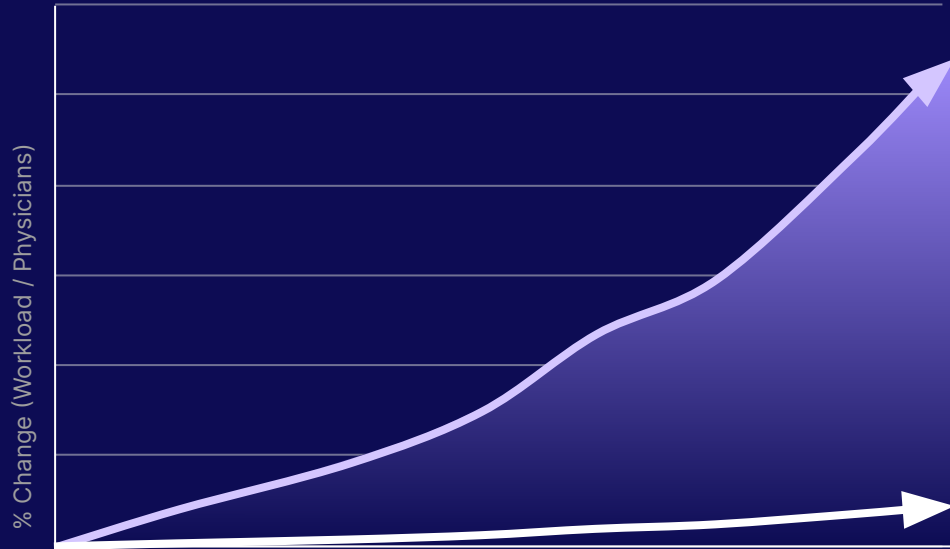
**„We should
stop training
radiologists
now!“**

- Geoffrey Hinton, 2016

<https://www.youtube.com/watch?v=2HMPRXstSvQ>

Current Demand-Supply-Gap Challenge

Radiology under Pressure



Source: RSNA Radiology Workforce 2019, DESTATIS 2020

Workload increase of

2.5x

In the last 10 years

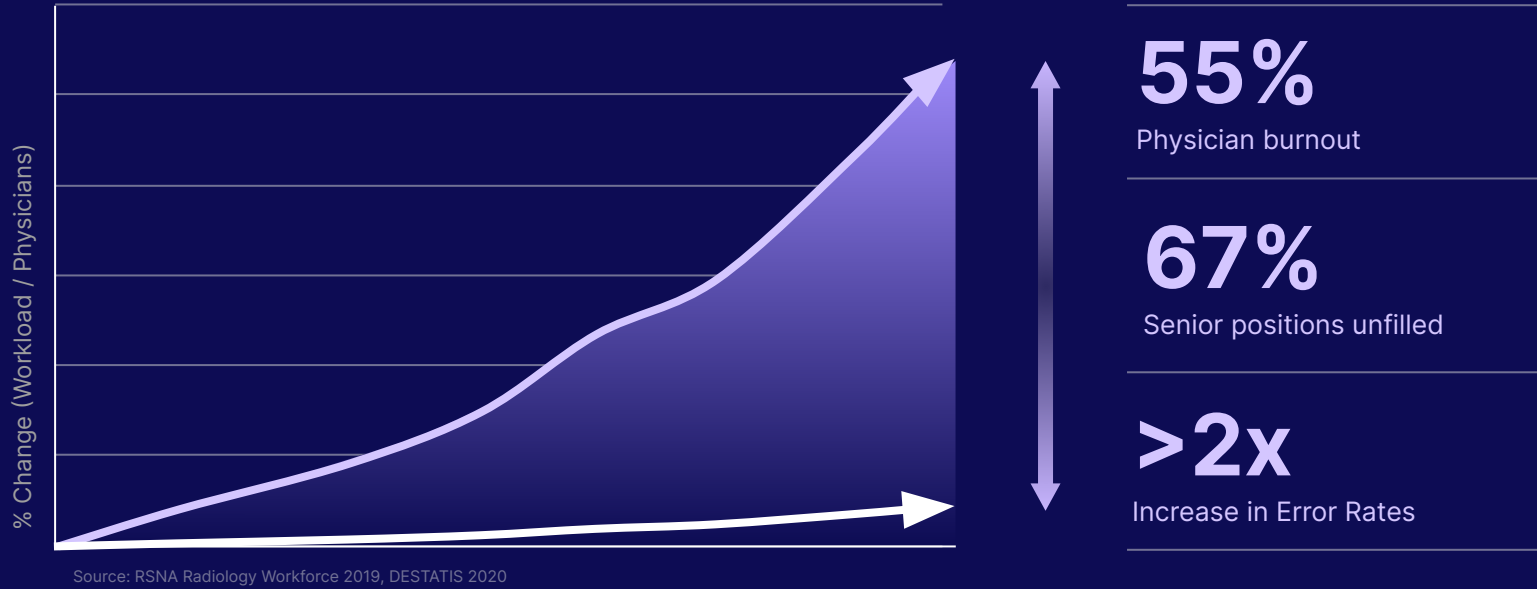
On Average only

1.1x

In number of Radiologists

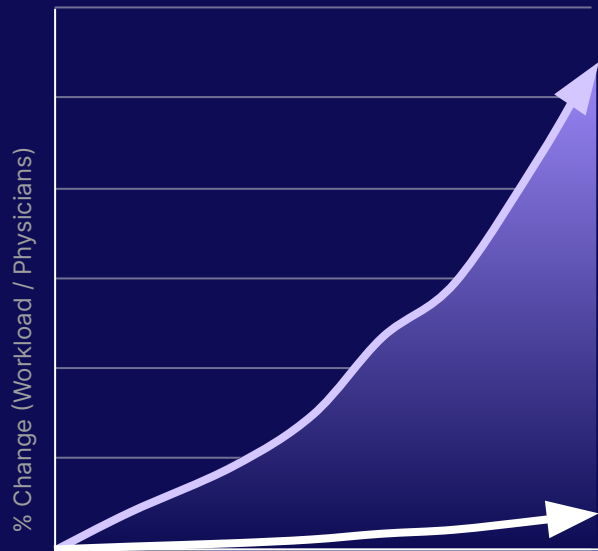
Current Demand-Supply-Gap Challenge

Radiology under Pressure



AI can fill the demand-supply gap

by making radiologists ...



Source: RSNA Radiology Workforce 2019, DESTATIS 2020

AI

... More **Efficient**

AI for routine tasks

e.g. high volume use cases

... More **Accurate**

AI enhancing doctors

e.g. head CT diagnosis

... **Faster** in decisions

AI augmenting doctors

e.g. MS quantification

AI as safety net

e.g. emergency care

AI for routine tasks

Example

Mammography screening

A. Current process:

Each mammogram read by
two radiologists



B. Process with AI:

Mammogram read by only
one radiologist plus AI



[1] Mattie Salim et al., External Evaluation of 3 Commercial Artificial Intelligence Algorithms for Independent Assessment of Screening Mammograms. JAMA Oncol. (2020).

[2] McKinney et al. International evaluation of an AI system for breast cancer screening. Nature (2020).

AI for routine tasks

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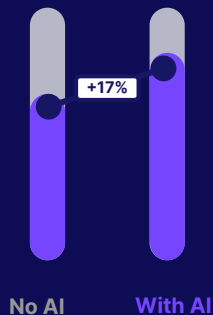


B. Process with AI:

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Cancer Detection
Rate [1]



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AI for routine tasks

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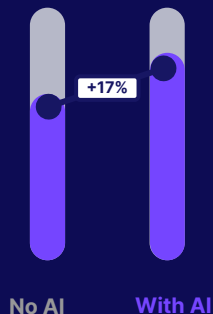


B. Process with AI:

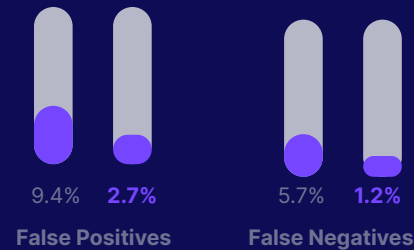
Mammogram read by only
one radiologist plus AI



Cancer Detection
Rate [1]



Doctor vs. AI
Performance [2]



[1] Mattie Salim et al., External Evaluation of 3 Commercial Artificial Intelligence Algorithms for Independent Assessment of Screening Mammograms. JAMA Oncol. (2020).

[2] McKinney et al. International evaluation of an AI system for breast cancer screening. Nature (2020).

AI enhancing doctors

Example

Diagnosis of CT Brain scans

A. Current process:

Each cCT read by one
radiologists



B. Process with AI:

cCT read by one
radiologist plus AI



AI enhancing doctors

Example

Diagnosis of CT Brain scans

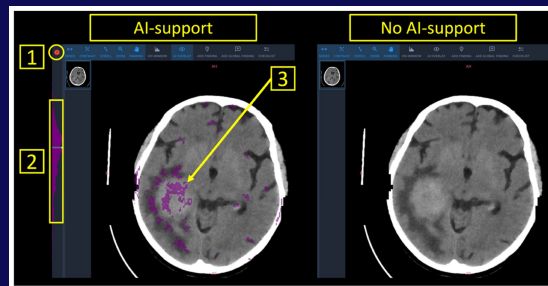
A. Current process:

Each cCT read by one
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B. Process with AI:

cCT read by one
radiologist plus AI



AI enhancing doctors

Example

Diagnosis of CT Brain scans

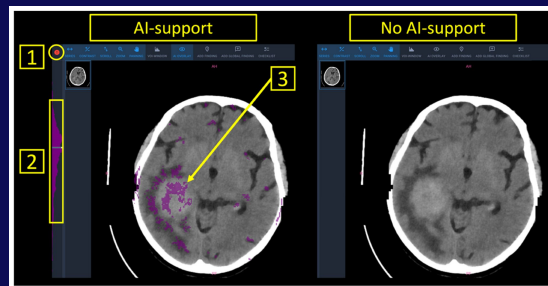
A. Current process:

Each cCT read by one radiologists

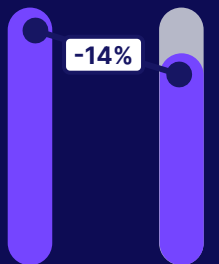


B. Process with AI:

cCT read by one radiologist plus AI



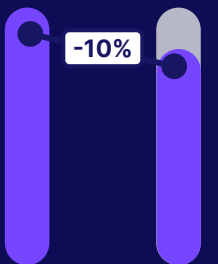
Reading Time
(Inexperienced)



No AI

With AI

Reading Time
(Experienced)



No AI

With AI

AI enhancing doctors

Example

Diagnosis of CT Brain scans

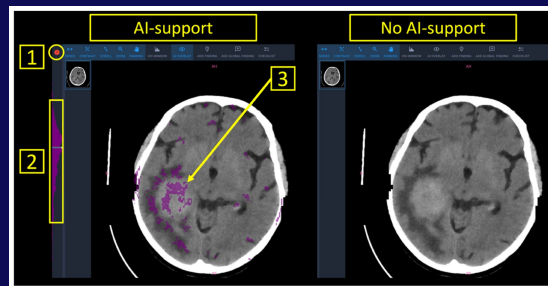
A. Current process:

Each cCT read by one radiologists

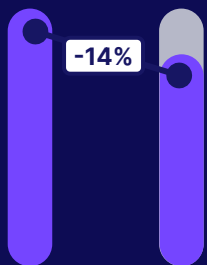


B. Process with AI:

cCT read by one radiologist plus AI



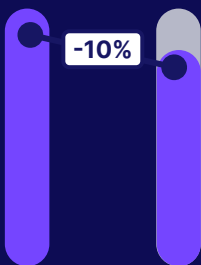
Reading Time
(Inexperienced)



No AI

With AI

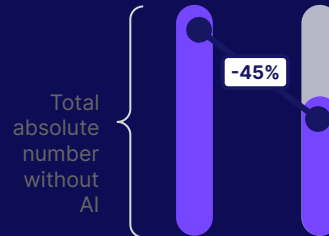
Reading Time
(Experienced)



No AI

With AI

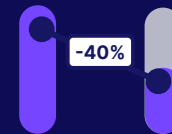
Missed Findings
(Inexperienced)



No AI

With AI

Missed Findings
(Experienced)



No AI

With AI

AI as safety net

Example

Prioritisation based on cCTs

A. Current process:

Radiologist is working
through chronologically



B. Process with AI:

Worklist prioritised based
on AI



AI as safety net

Example

Prioritisation based on cCTs

A. Current process:

Radiologist is working through chronologically



B. Process with AI:

Worklist prioritised based on AI

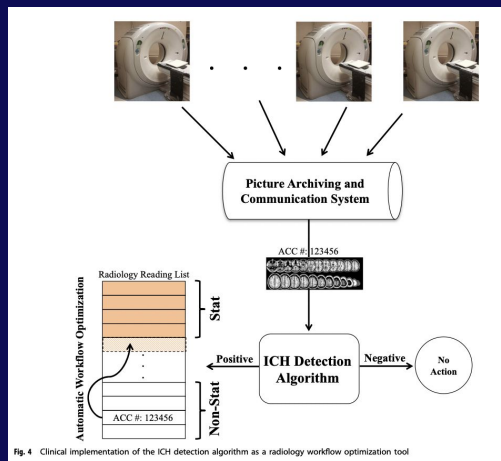


Fig. 4 Clinical implementation of the ICH detection algorithm as a radiology workflow optimization tool

AI as safety net

Example

Prioritisation based on cCTs

A. Current process:

Radiologist is working through chronologically



B. Process with AI:

Worklist prioritised based on AI

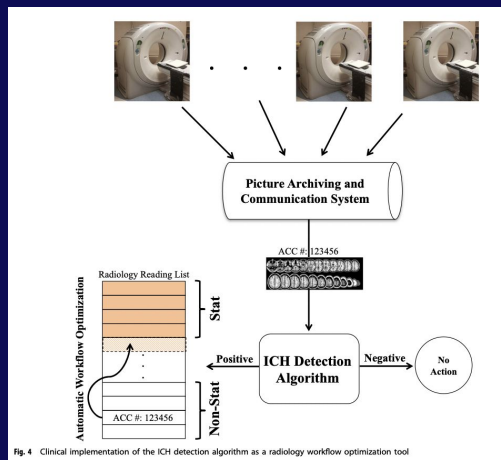


Fig. 4 Clinical Implementation of the ICH detection algorithm as a radiology workflow optimization tool

Time to Diagnosis



No AI

With AI

Decreased time to diagnosis by up to 96%

AI augmenting doctors

Example

Brain MRI scans

A. Current process:

Radiologist is diagnosing as
usual



B. Process with AI:

Radiologist receives additional
quantification through AI



[5] J Albers et al. Real-life evaluation of the AI-based Neuroradiology Suite mdbrain. Accepted for ECR2022; n=285

[6] J Rudolph et al. Artificial Intelligence substantially improves dementia diagnosis – Added diagnostic value of rapid brain volumetry. RSNA 2021 NR02-A6

AI augmenting doctors

Example

Brain MRI scans

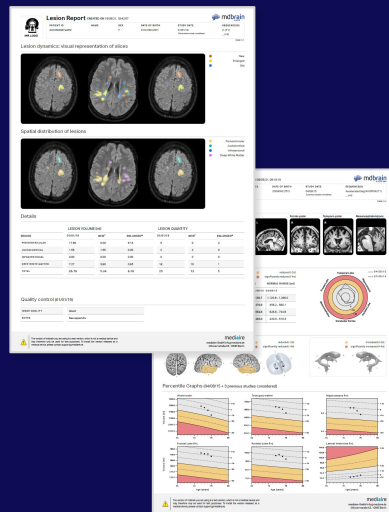
A. Current process:

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AI augmenting doctors

Example

Brain MRI scans

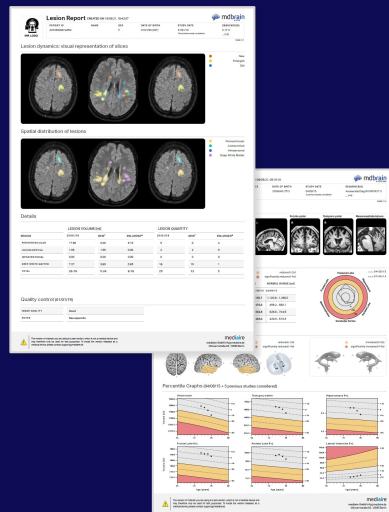
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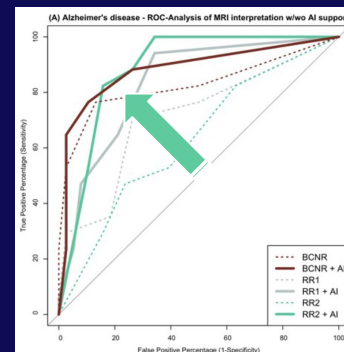


B. Process with AI:

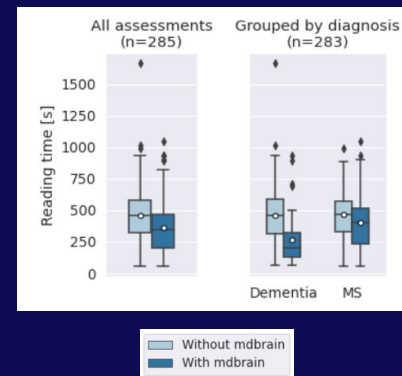
Radiologist receives additional quantification through AI



Increased
diagnostic
accuracy



Reading time
reduced
by ~25%
Effect size
largest in brain
volumetry (-57%)



[5] J Albers et al. Real-life evaluation of the AI-based Neuroradiology Suite mdrbrain. Accepted for ECR2022; n=285

[6] J Rudolph et al. Artificial Intelligence substantially improves dementia diagnosis – Added diagnostic value of rapid brain volumetry. RSNA 2021 NR02-A6

3 Key Challenges of AI in Radiology

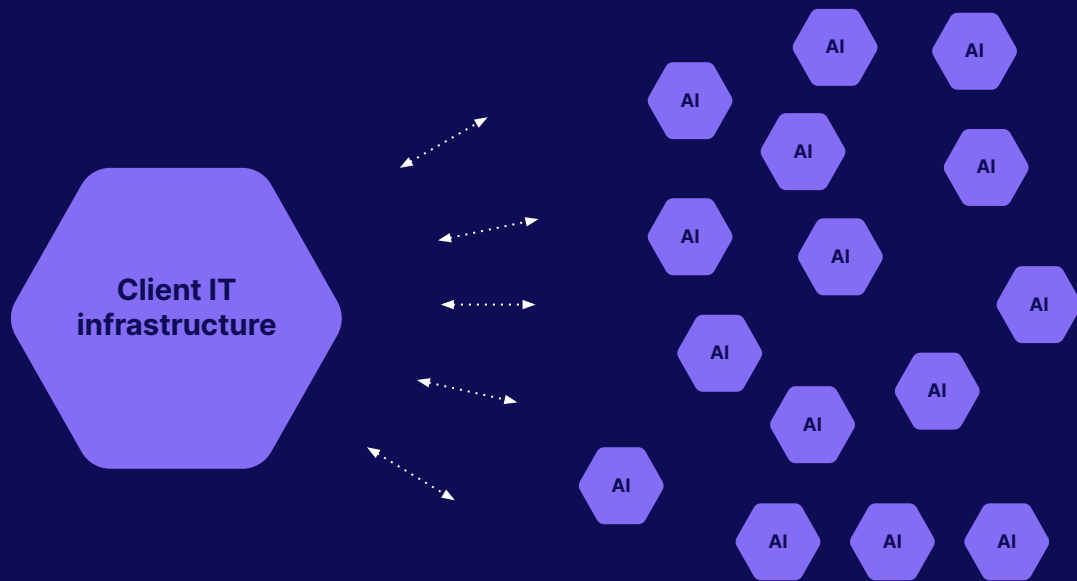
3 Key Challenges of AI in Radiology

1

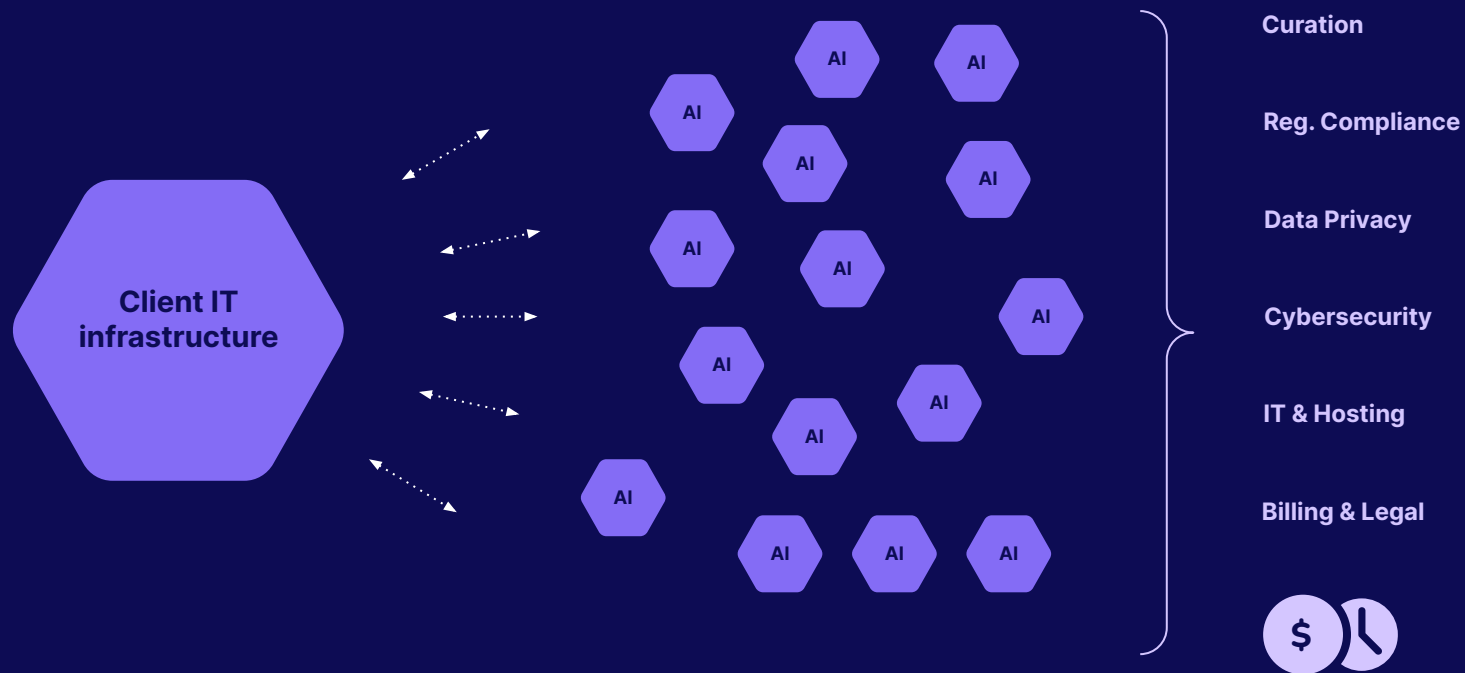
Choosing the right AI tool(s)

Any choice comes at a high cost

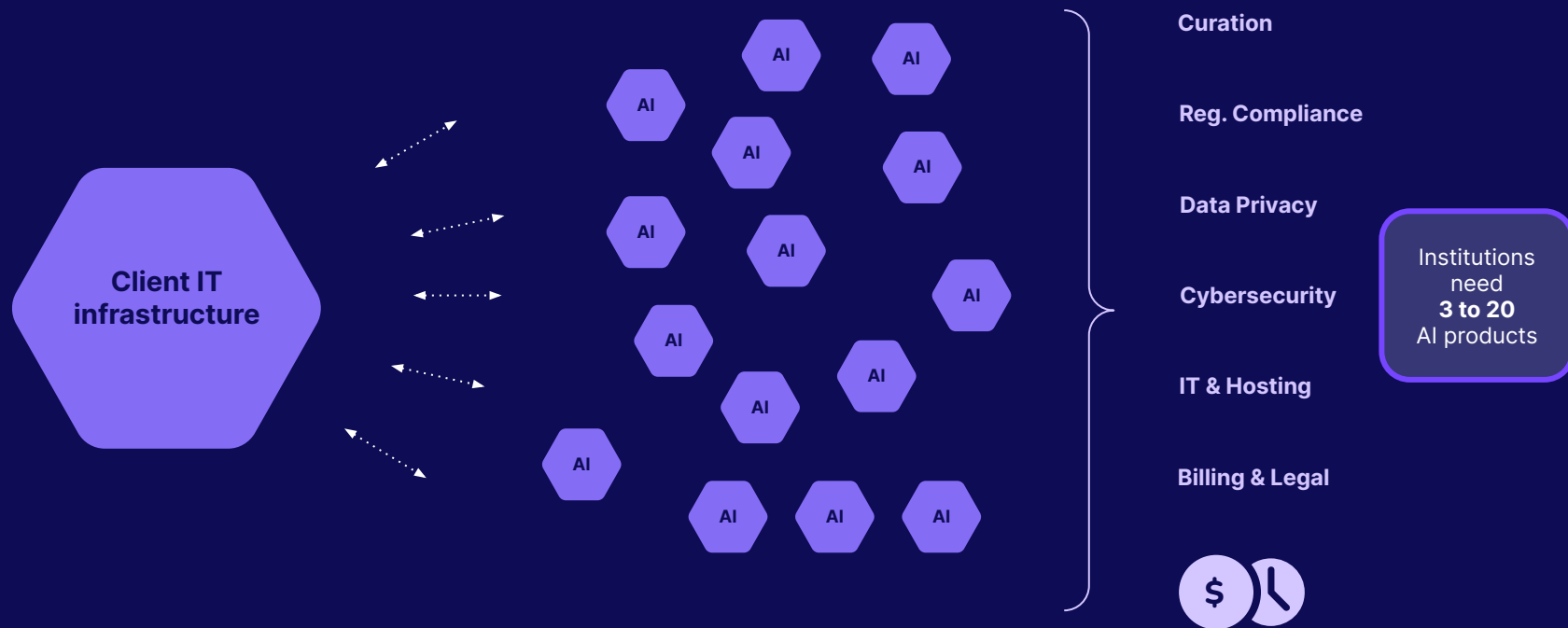
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Choosing the right AI tool(s)



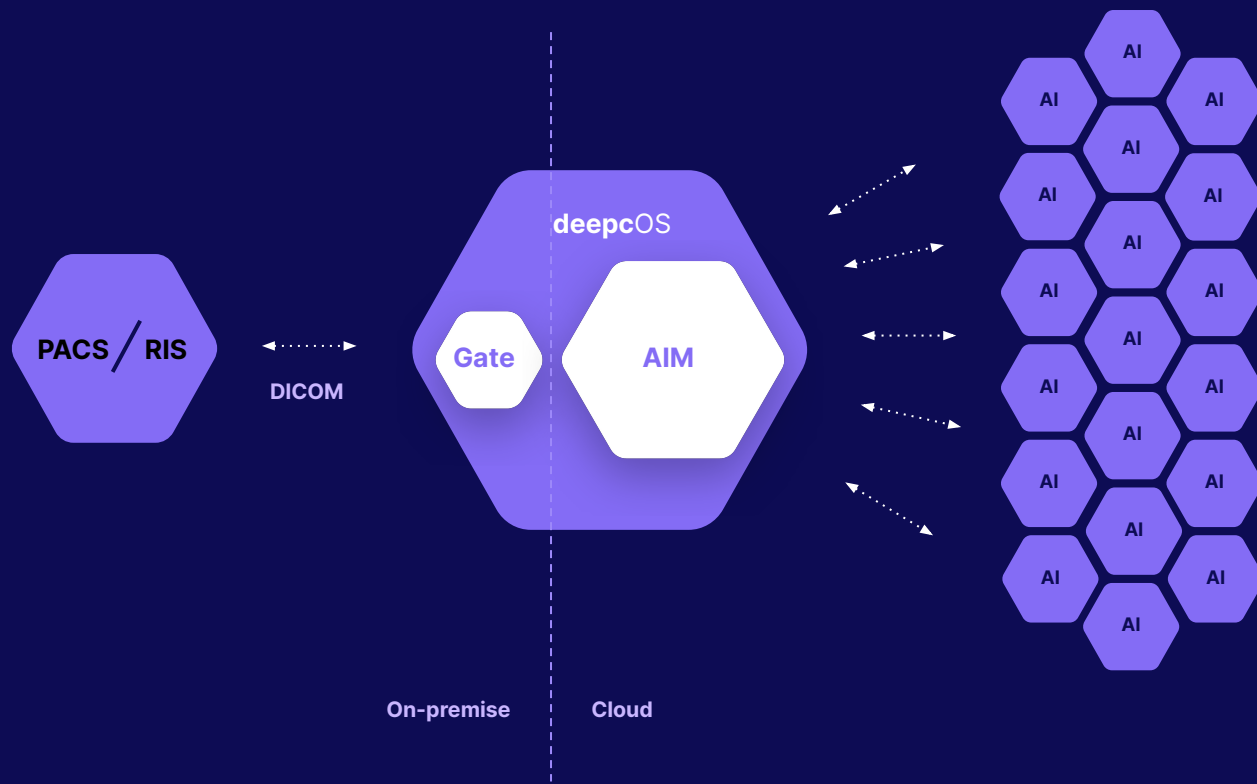
Choosing the right AI tool(s)



Solution

deepcOS AIM

Provides a single-installation solution to easily
integrate AI into clinical workflows



3 Key Challenges of AI in Radiology

1

Choosing the right AI tool(s)

Any choice comes at a high cost

2

Integrating AI into the workflow

Radiologists will not buy in into changing their existing workflow

Integrating it into the workflow

Example

You want to use AI to prioritize stroke and bleeding cases in your workflow

**Display 1:
Worklist**



**Display 2:
Image Study**



**Display 3:
Report writing**



**In addition:
Ringing phone**



Integrating it into the workflow

Example

You want to use AI to prioritize stroke and bleeding cases in your workflow

**Display 1:
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Stroke



Bleeding

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Stroke



Bleeding

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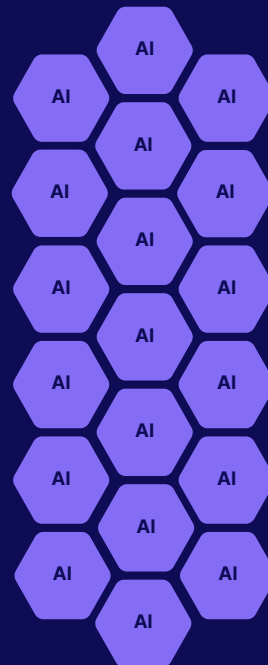
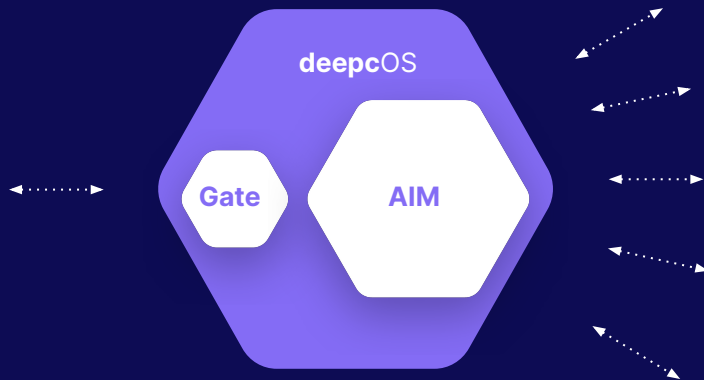
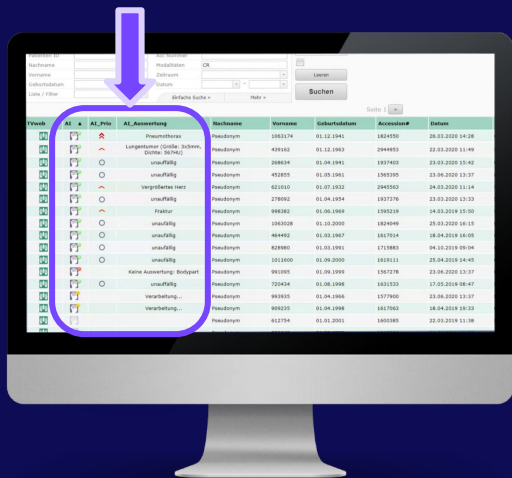
**In addition:
Ringing phone**



Deeply integrating with existing workflows

Display of

- Processing Status
- Prioritization Column
- AI Preview of Diagnoses



3 Key Challenges of AI in Radiology

1

Choosing the right AI tool(s)

Any choice comes with a buy-in

2

Integrating AI into the workflow

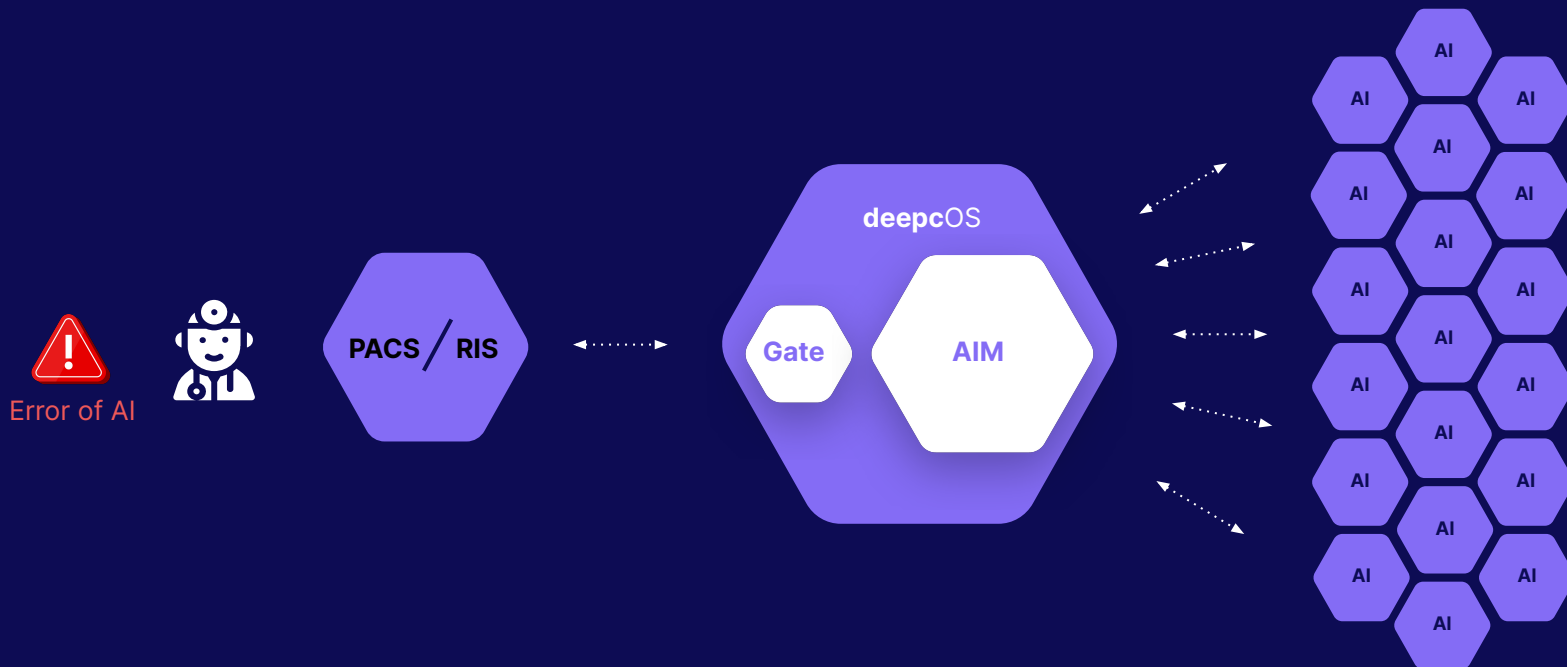
Radiologists will not buy in into changing their existing workflow

3



The need for giving feedback

It should be built into the system

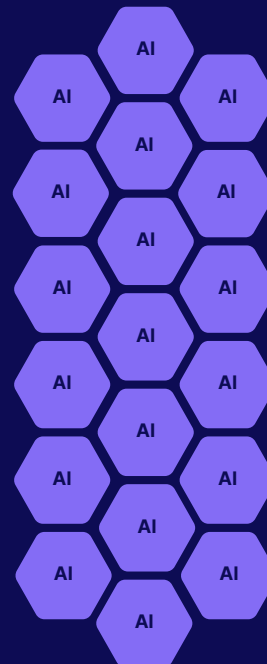
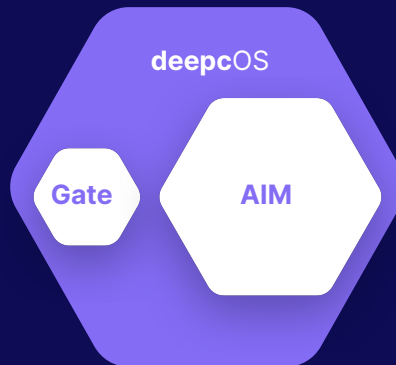
Establish a feedback loop





Establish a feedback loop

Series	Approve or Reject AI	Push to PACS
 Series XYZ	APPROVE REJECT	<input type="checkbox"/>
 Series ABC	APPROVE REJECT	<input checked="" type="checkbox"/>
		CANCEL SUBMIT

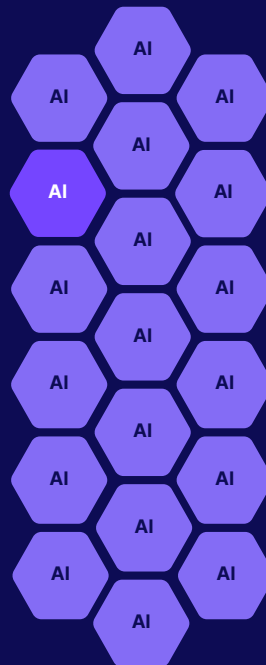
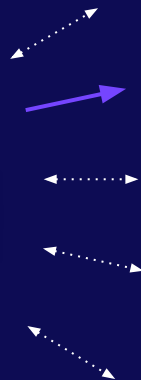
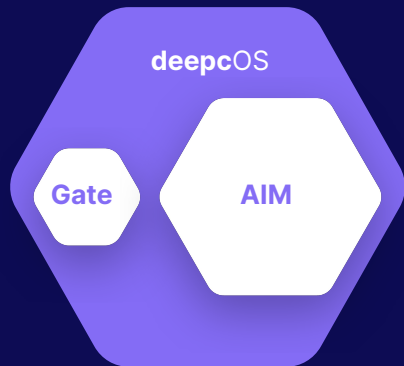

Error of AI



Establish a feedback loop

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 Series XYZ	APPROVE REJECT	<input type="checkbox"/>
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		CANCEL SUBMIT


Error of AI



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It should be built into the system



Thank You



Julia Moosbauer, MSc Data Science

COO, Co-Founder



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81671 Munich, Germany



[in/juliamoosbauer/](https://www.linkedin.com/company/deepc)

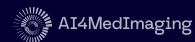


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julia.moosbauer@deepc.ai

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