AI for breast imaging

Better, faster, less!

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"Radiologists who do AI will replace radiologists who don't"

- A certain Dutch radiologist (...and many others)

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Disclosures

Research Agreements:	Siemens Healthcare Canon Medical Systems
Speaking Agreements:	Siemens Healthcare Hologic

ScreenPoint Medical is a spin-off company from my Department. I have no financial relationship with ScreenPoint.

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AXTI Lab
(Advanced X-ray Tomographic Imaging)

Ritse Mann

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AI for Breast Imaging

Why now?
Faster!
Better!
Less!
yes, also good ol' physics!

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Background

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Digital Breast Tomosynthesis (DBT)

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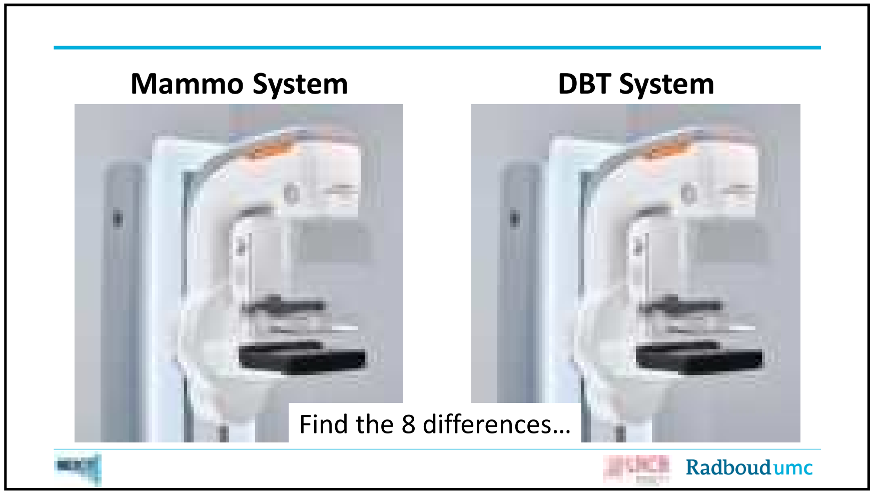
Mammo System
DBT System
Find the 8 differences…
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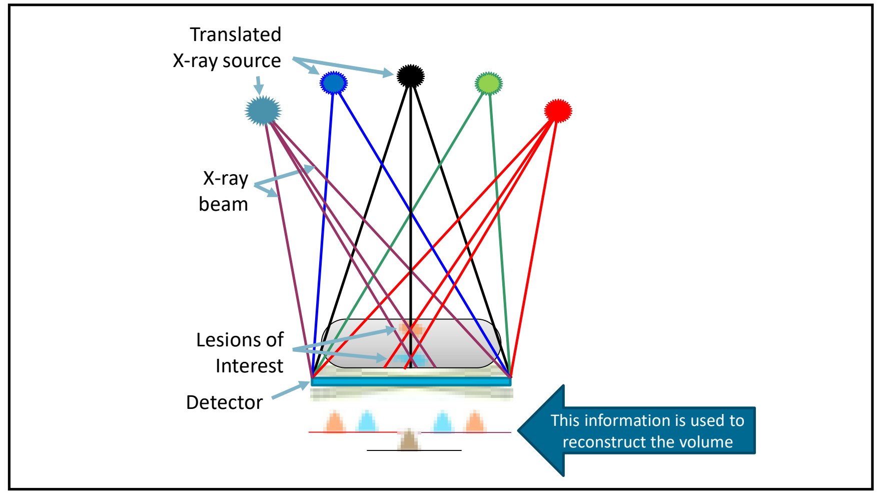
Translated
X-ray source
X-ray
beam
Lesions of
Interest
Detector
This information is used to
reconstruct the volume

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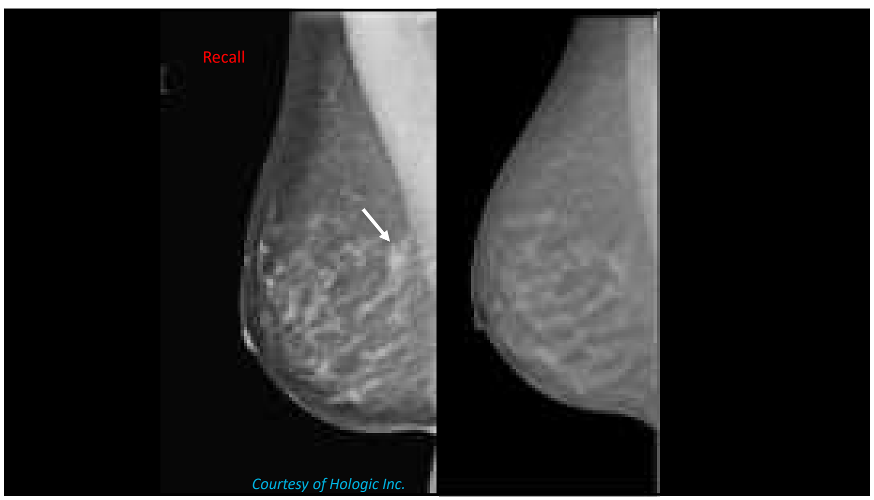
Recall
Courtesy of Hologic Inc.

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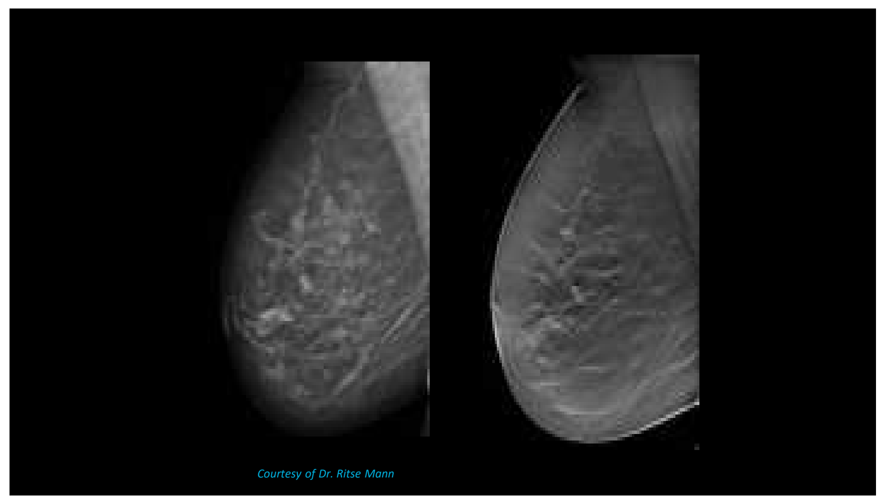
Courtesy of Dr. Ritse Mann

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Courtesy of Dr. Ritse Mann

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Institution-based

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Single Reading

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Population-based Screening

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Digital Mammography

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Double Reading

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Referral Rate:
2.4%

Cancer Detection Rate:
6.8 per 1,000

Interval Cancer Rate:
2.2 per 1,000

Visible Interval Cancers:
~50%

2 healthy women per cancer case recalled

We could (try to) do better!

(and faster and less)

Why now?

Running out of screening radiologists

DBT takes time

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Image from https://blogs.nvidia.com/blog/2016/07/29/

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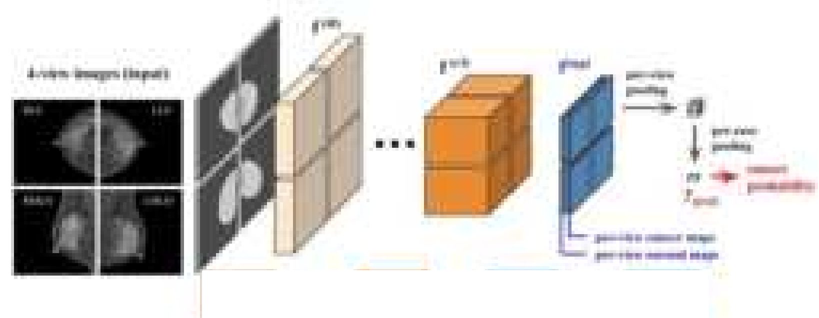
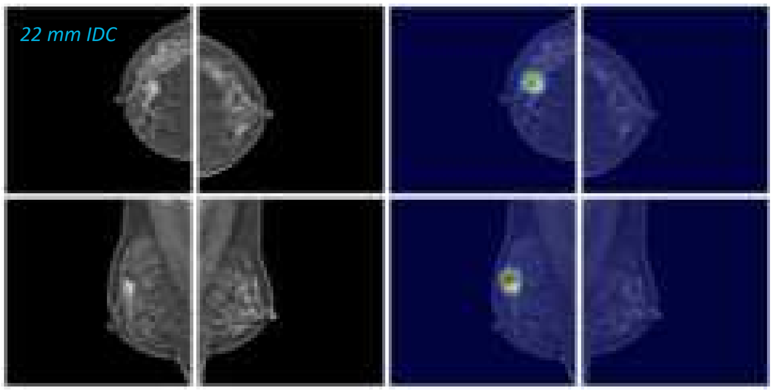


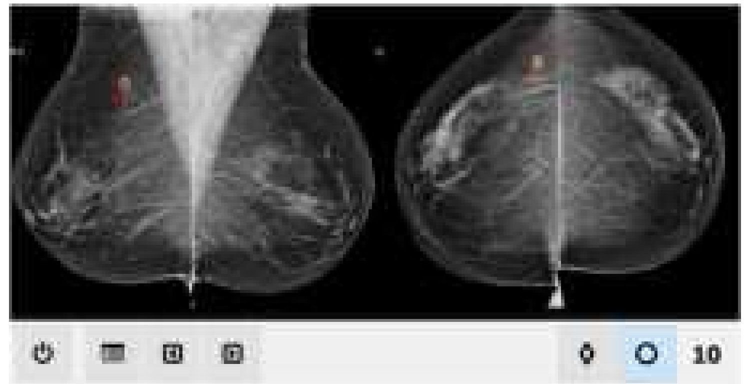
Kim et al, Scientific Reports, 2018.

36



Kim et al, Scientific Reports, 2018.

37



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How good is it?

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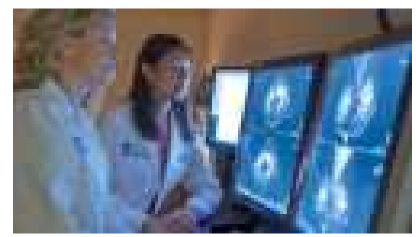
AI system

Breast screening radiologists



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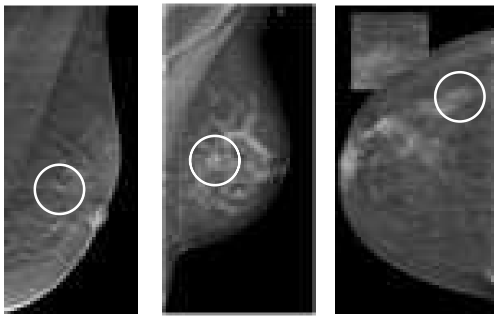
Task: detect breast cancer in mammography



Case level

Digital Mammography Cases

9 Previous multi-reader multi-case retrospective studies

Radiology

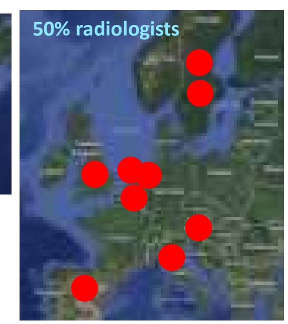
European Radiology

INVESTIGATIVE RADIOLOGY

FDA

Rodriguez Ruiz et al, JNCI, 2019.

Datasets



Varied datasets characteristics & sizes

Different radiologists

Rodriguez Ruiz et al, JNCI, 2019.

Breast screening radiologists

Varied experience with screening:
1-45 years
avg. 10 years

45

Total numbers

2,652 exams

653 malignant (i.e. enriched sets)

50% screening/50% diagnostic

46

Total numbers

101 radiologists

47

Total numbers

28,296 independent interpretations

48

Total numbers

4 vendors

GE
Hologic
Philips
Siemens

Rodriguez Ruiz et al, JNCI, 2019.

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AI SYSTEM

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AI system

Transpara 1.4.0
(ScreenPoint Medical, Nijmegen, the Netherlands)

Based on deep learning algorithms

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Statistical analysis

Non-inferiority hypothesis in terms of area under the ROC curve (AUC)

Margin 0.05

Rodriguez Ruiz et al, JNCI, 2019.

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RESULTS

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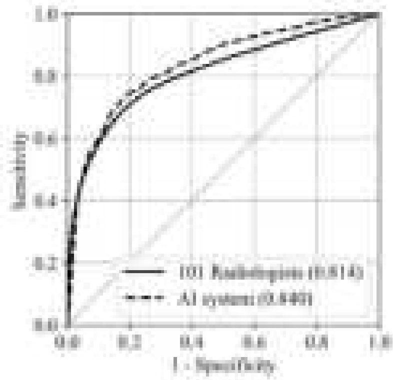

AUC AI system = 0.840
(95% CI = 0.820-0.860)
AUC 101 radiologists = 0.814
(95% CI = 0.787-0.841)

95% CI of difference = [-0.003,0.055]

Rodriguez Ruiz et al, JNCI, 2019.

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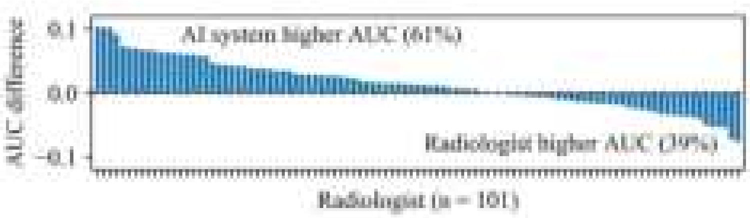

Rodriguez Ruiz et al, JNCI, 2019.

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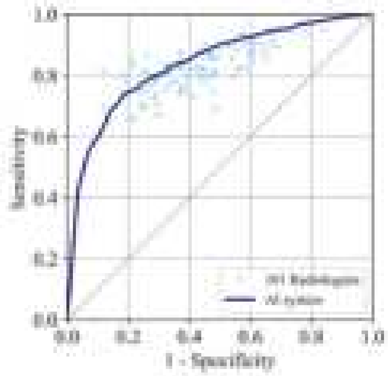

Rodriguez Ruiz et al, JNCI, 2019.

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Limitations

Not all datasets were bilateral and with priors

Rodriguez Ruiz et al, JNCI, 2019.

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AI doesn't consider priors…

…but…

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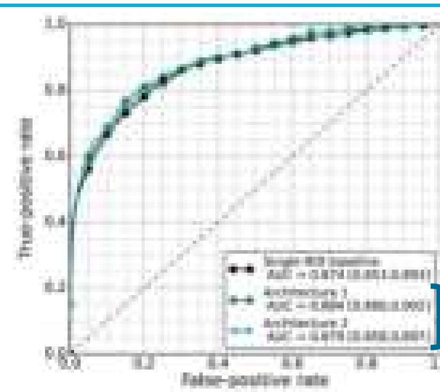

with prior analysis

Kooi and Karssemeijer, JMI, 2017.

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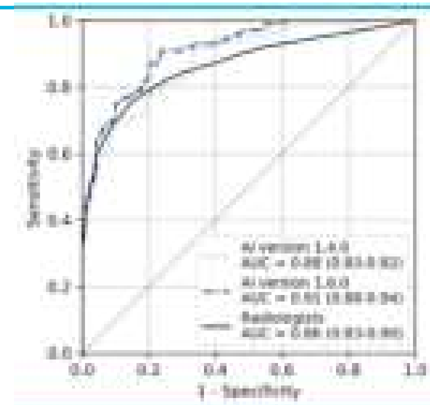
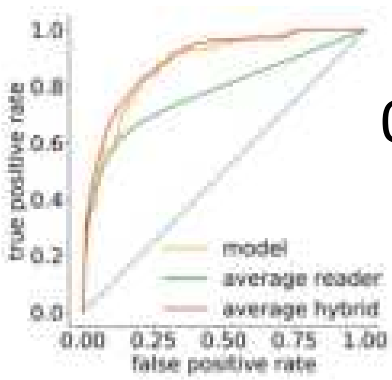
Better implementation?

OR

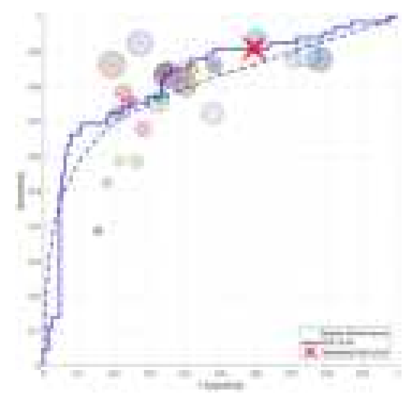
Is the info already there?





0.778 vs. 0.876
+0.098

Wu et al, IEEE Transactions on Medical Imaging, 2019.



Avg. of radiologists:
- sensitivity: 77.0%
- specificity: 62.7%

AI system:
- sensitivity: 91%
- specificity: 41%

Conant et al, Radiology: Artificial Intelligence, 2019.

Enriched data sets

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Retrospective reads

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We’re on our way…

…to where?

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Faster!

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RT(DBT) = 2.0*RT(DM)

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AI-assisted reading

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AI-assisted reading

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Reading time reduction

64.1 s → 30.4 s

-52.7%*

Conant et al, Radiology: Artificial Intelligence, 2019.

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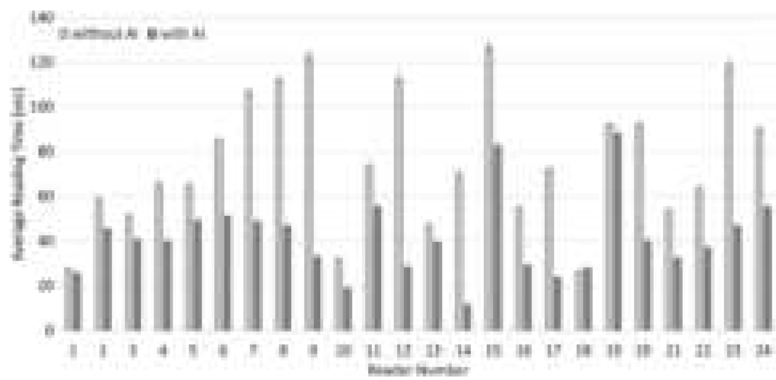

Conant et al, Radiology: Artificial Intelligence, 2019.

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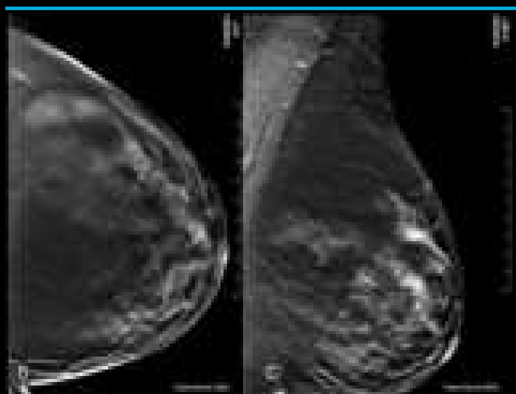

5-mm IDC with associated DCIS

no AI: 110.3 s

with AI: 62.3 s

Conant et al, Radiology: Artificial Intelligence, 2019.

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AI-assisted rad reading

OR

rad-assisted AI reading?

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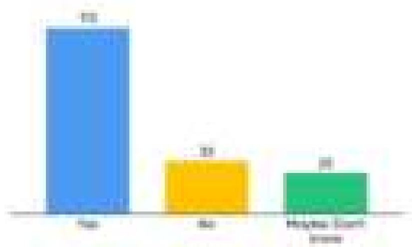
Is a 50% reduction in time only possible if we give up human search?



170

170 radiologists et al on their phones, RSNA Annual Meeting, Arie Crown, 2019.

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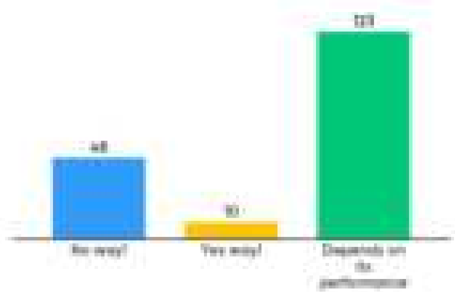
Is it acceptable for only the AI to do the search?



181

181 radiologists et al on their phones, RSNA Annual Meeting, Arie Crown, 2019.

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Better!

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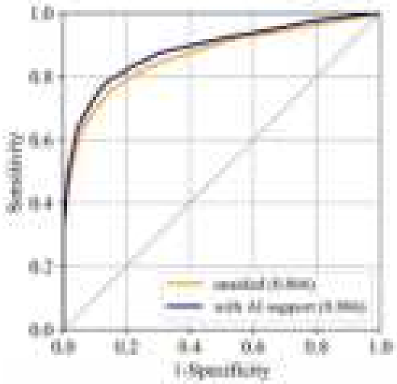

DM:
0.866 [0.83,0.90]
➔ 0.886 [0.85,0.92]

+0.020
[0.007, 0.032]
P = 0.002

Rodriguez-Ruiz et al, Radiology, 2019.

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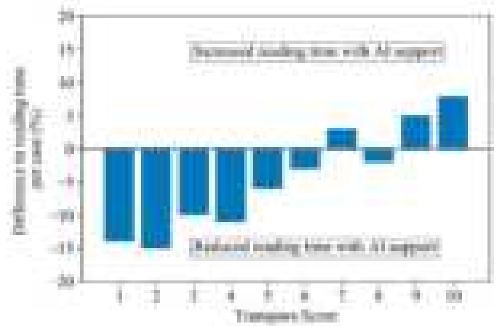

Unaided: 146 s
w/ AI: 149 s
P=0.15

Rodriguez-Ruiz et al, Radiology, 2019.

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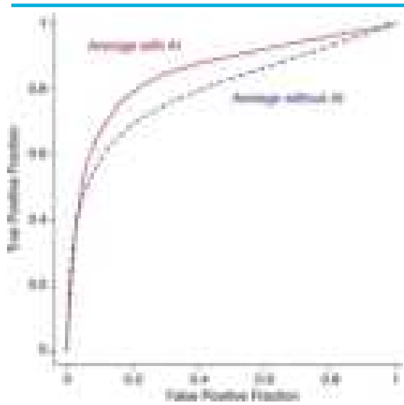

DBT:
53% reduction:

0.795 ➔ 0.852
+0.057*

Conant et al, Radiology: Artificial Intelligence, 2019.

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Less!

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AI Assisted Reading vs. Standalone AI

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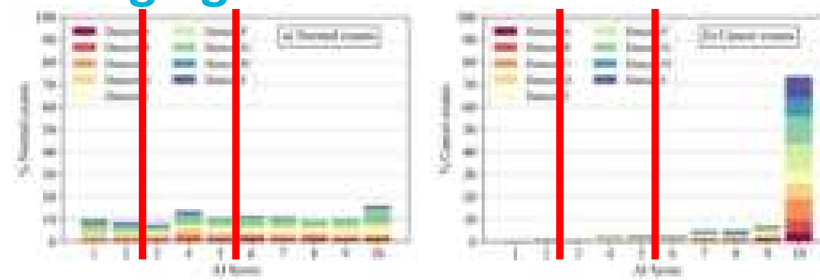
Triaging AI



Rodriguez Ruiz et al, Eur Radiol, 2019.

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47% decrease in cases

➔ -7% cancers

-27% false positives

Rodriguez Ruiz et al, Eur Radiol, 2019.

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87

20% decrease in cases

➔ -1% cancers

-5% false positives

Rodriguez Ruiz et al, Eur Radiol, 2019.

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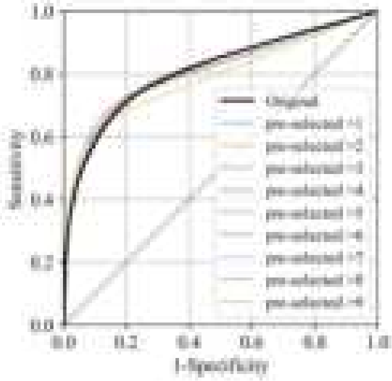

Rodriguez Ruiz et al, Eur Radiol, 2019.

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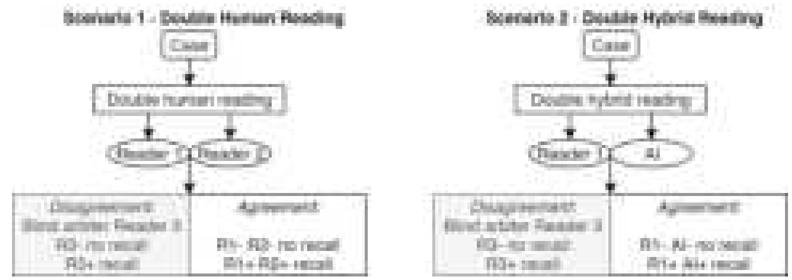

Rodriguez-Ruiz et al, International Workshop on Breast Imaging, Leuven, 2020

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	Scenario 1 – Double Human Reading	Scenario 2 – Double Hybrid Reading	Difference
Sensitivity (%)	81.5 (75.8, 87.3)	81.4 (75.3, 87.2)	-0.1 (-4.1, 3.9) P = 0.88
Specificity (%)	69.9 (68.4, 71.5)	75.2 (73.8, 76.7)	+5.3 (4.0, 6.7) P<0.001
Human Workload (%)	100	56 (55, 57)	-44 (-42, -45)

Rodriguez-Ruiz et al, International Workshop on Breast Imaging, Leuven, 2020

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All 8 missed cancers were “clearly visible”

Lång et al, European Congress of Radiology, Vienna,, 2019.

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Which cancers?

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How will you behave?

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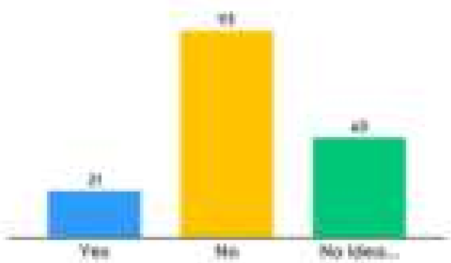
Will you read the same way after AI triaging?



159

159 radiologists et al on their phones, RSNA Annual Meeting, Arie Crown, 2019.

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NWO Applied and Engineering Sciences

aiREAD

Accurate and Intelligent Reading for EArlier breast cancer Detection

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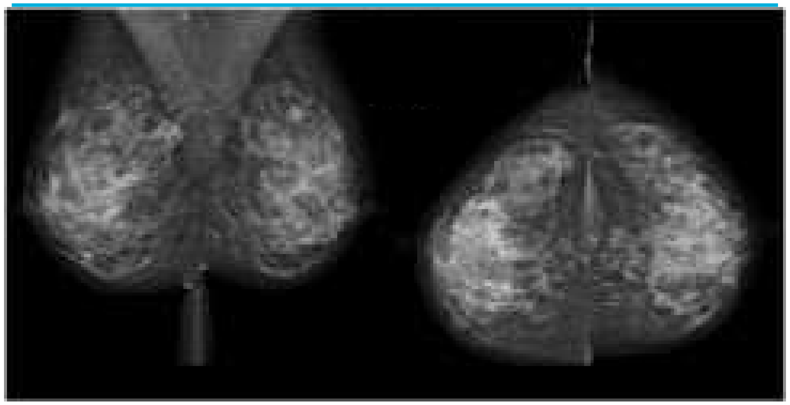
100



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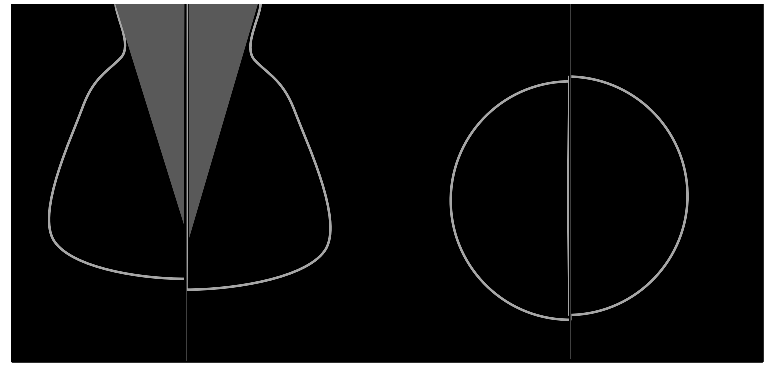

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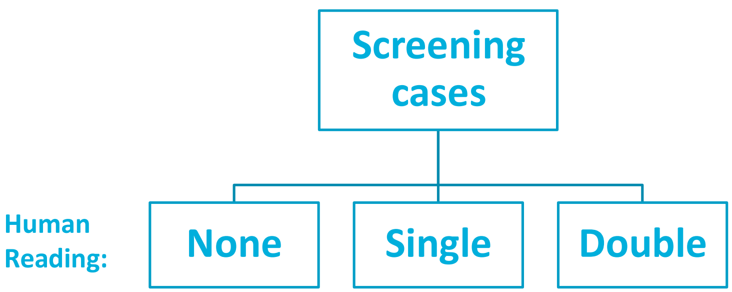

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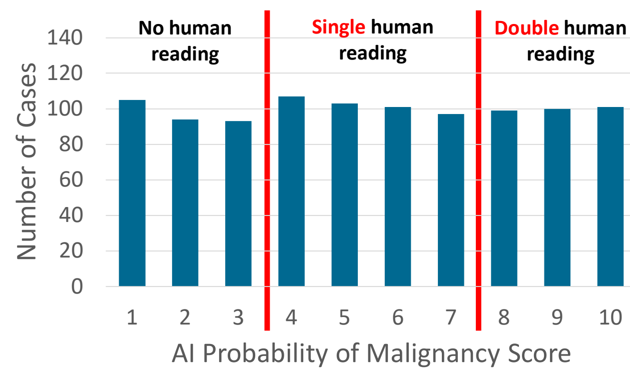

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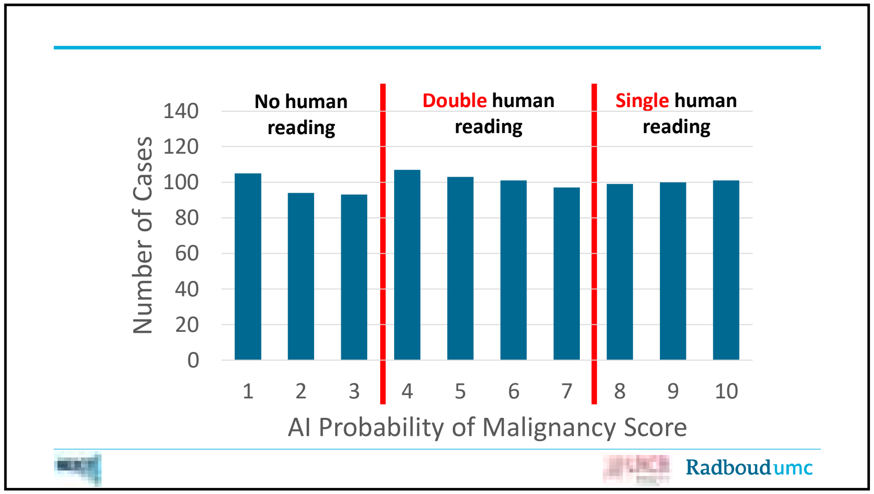

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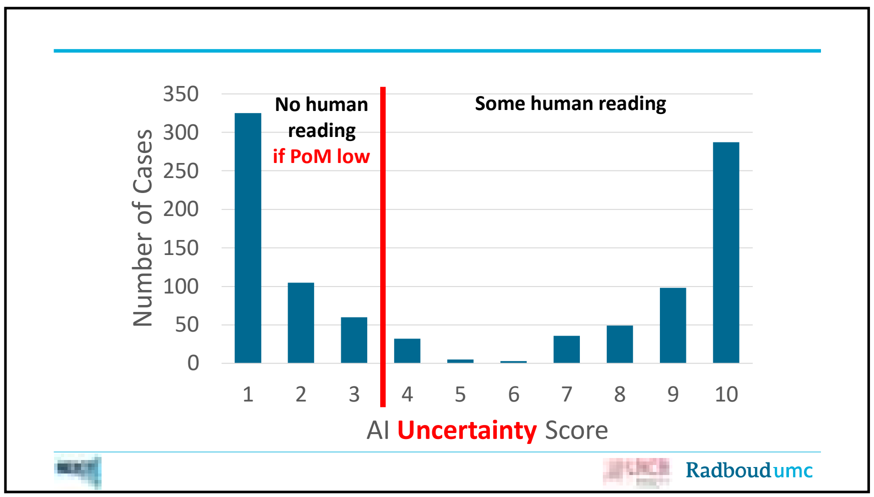

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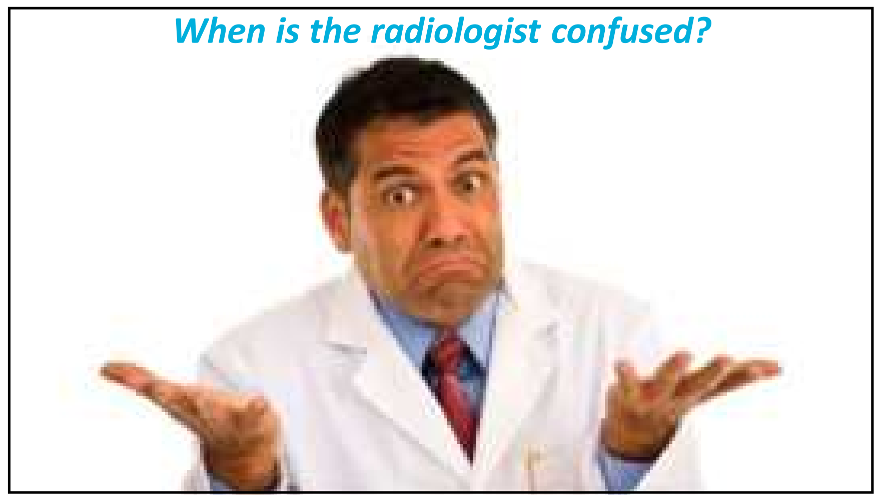

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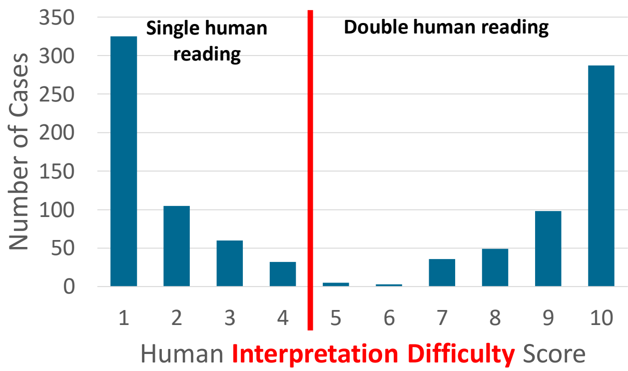

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I see it!!

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False negatives

	Tomo + Mammo -	Tomo - Mammo +
Visibility	13	0
Radiographic appearance	3	1
Interpretative error	3	6

Lång et al, Br J Radiol 2014;87:20140080

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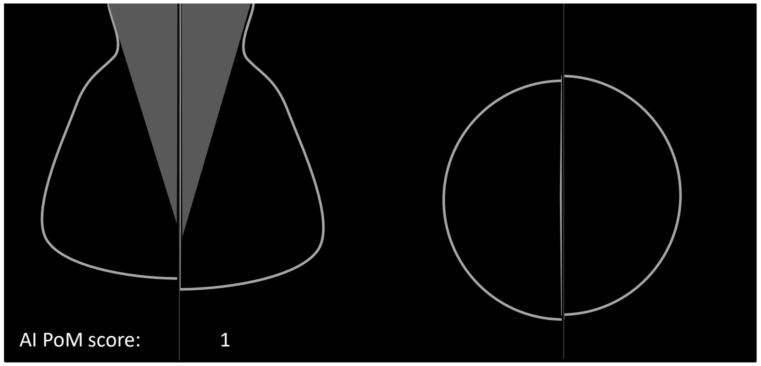

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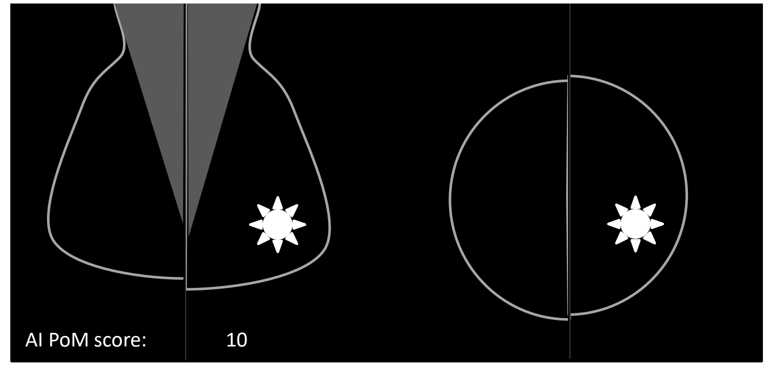

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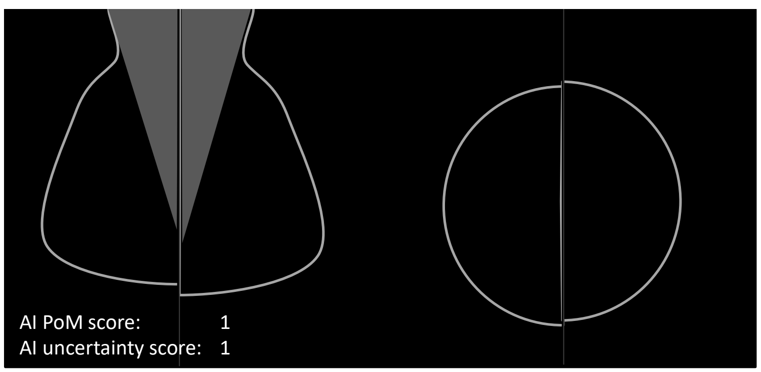

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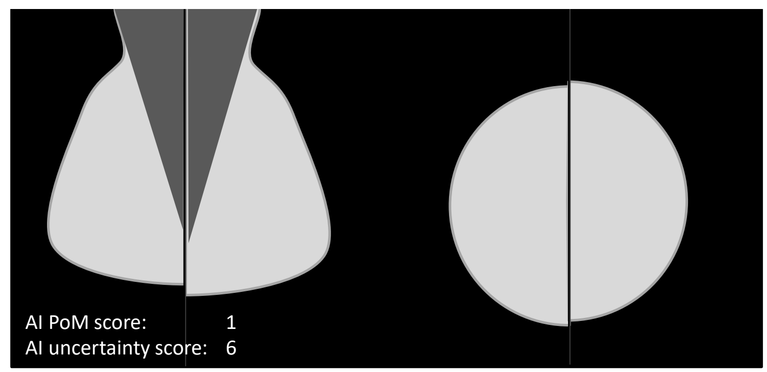

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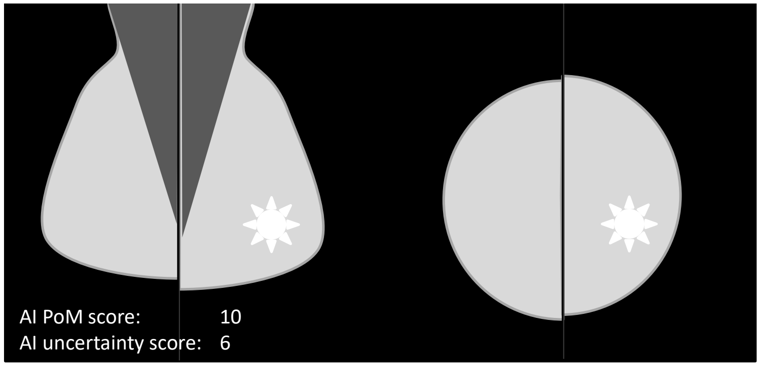

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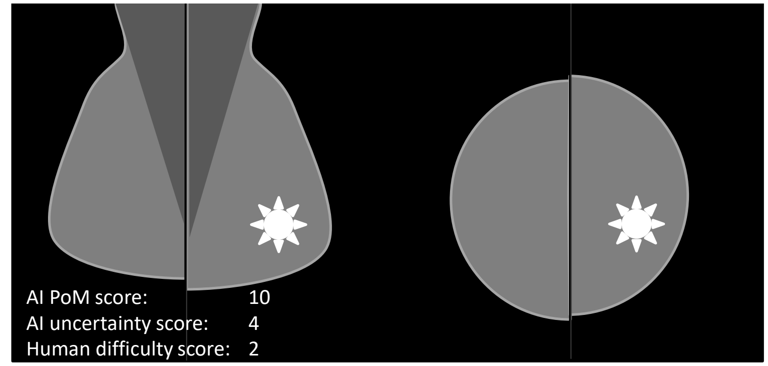

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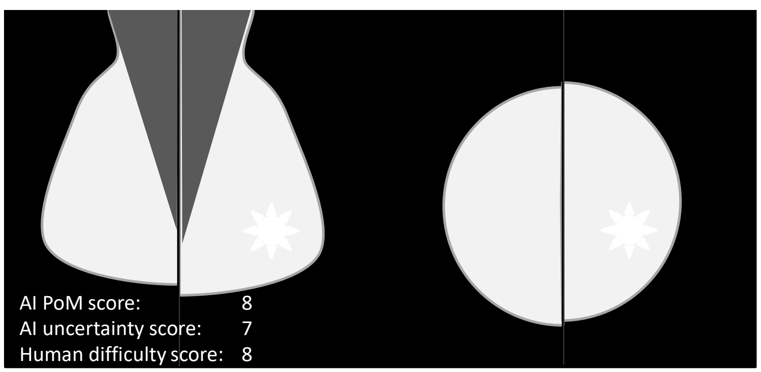

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AI for breast image interpretation

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Better?

”lab” results say yes

need for prospective screening-prevalence trials

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Faster?

yes!

is rad-assisted AI reading acceptable?

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Less?

triaging
single reading
other…

promising results, more needed

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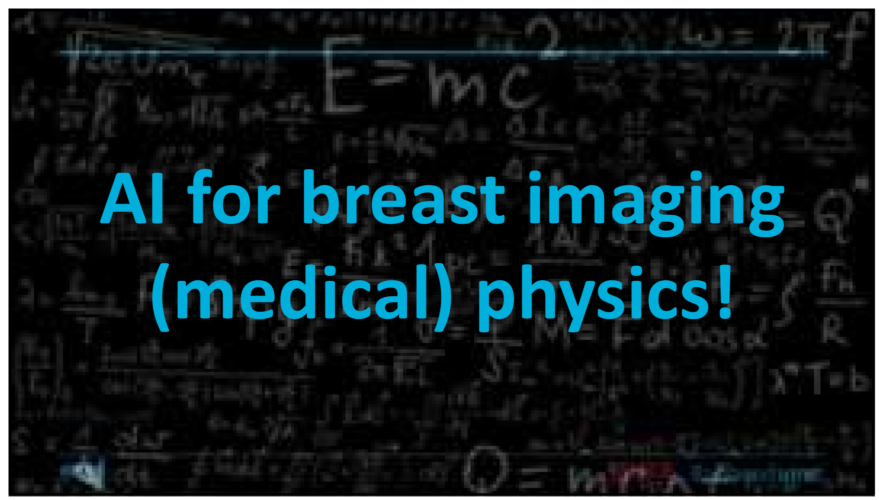

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X-ray scatter correction in DBT

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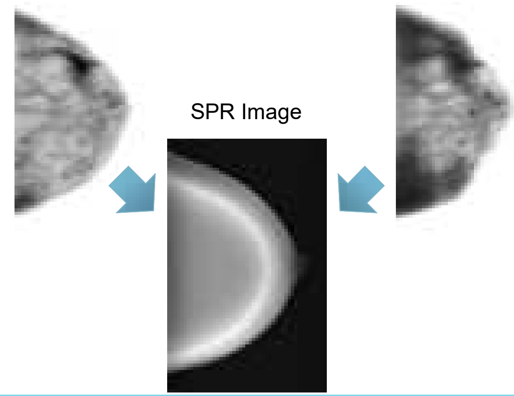
Low Glandular Density Breast

SPR Image

High Glandular Density Breast



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Acquisition of 3-D breast shape

Agasthya et al, AAPM 2015
Rodriguez-Ruiz et al, PMB, 2017

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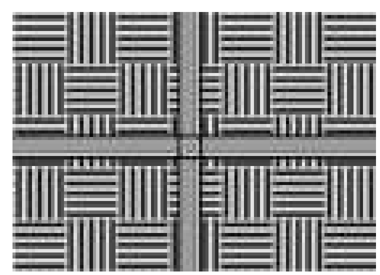
3-D scanner



Agasthya et al, AAPM 2015
Rodriguez-Ruiz et al, PMB, 2017

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Rodriguez-Ruiz et al, PMB, 2017

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Patient-based breast shape model

Rodriguez-Ruiz et al 2017, PMB

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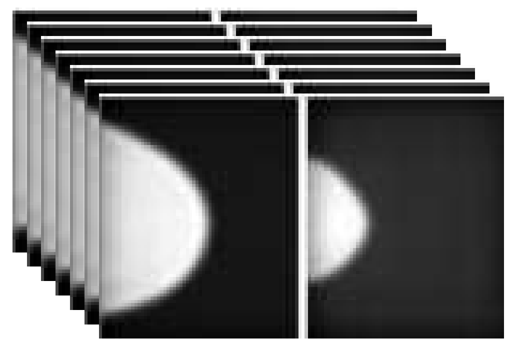

Rodriguez-Ruiz et al, ECR 2019

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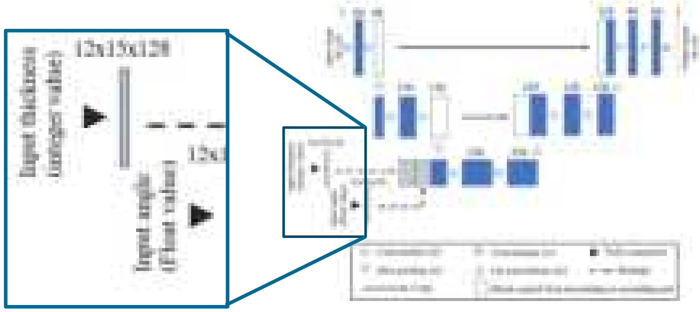
Modified u-net



Ronnberger et al, 2016, arxiv

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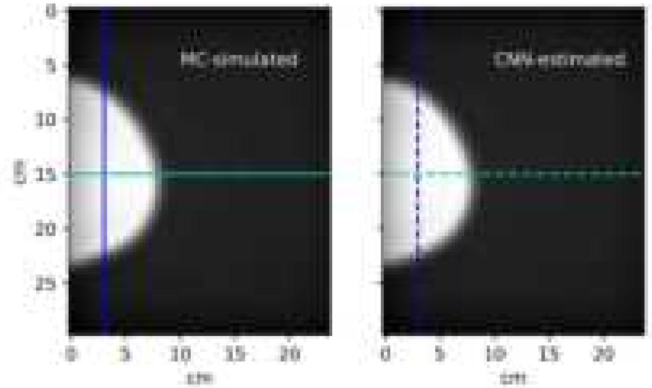

Rodriguez-Ruiz et al, ECR 2019

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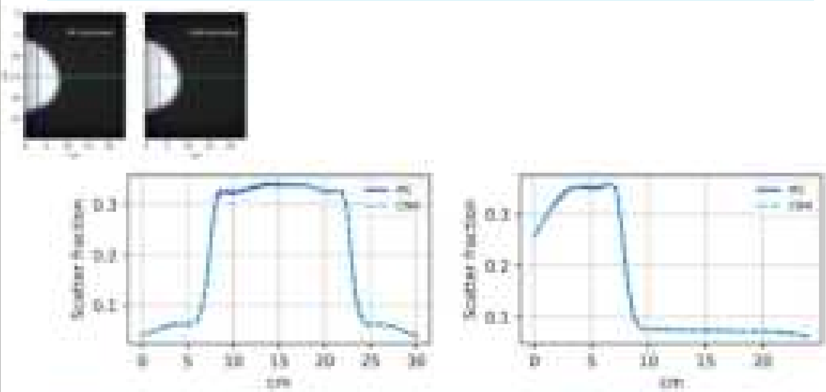

Rodriguez-Ruiz et al, ECR 2019

Radboudumc

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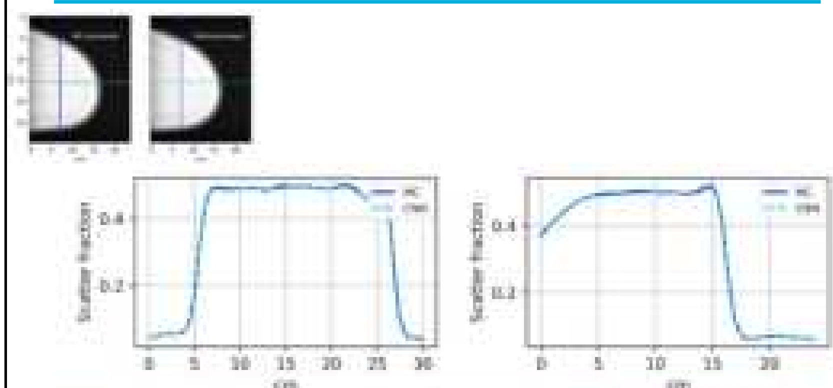

Rodriguez-Ruiz et al, ECR 2019

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Mean absolute error

All images:	0.9%
Only area inside breast:	0.4%
Only breasts > 60 mm thick:	1.0%

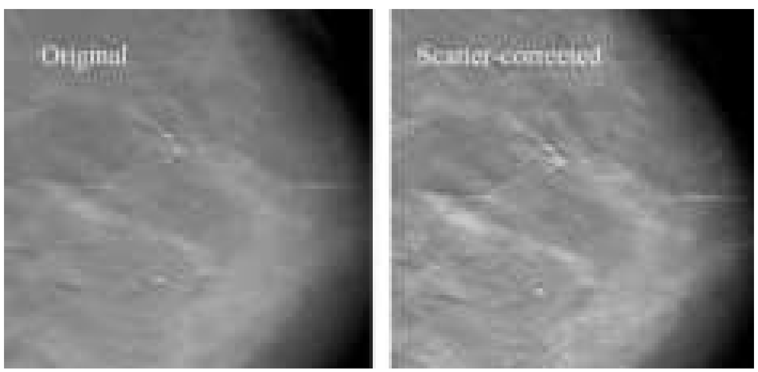
CNN modeling

1 GPU: **0.01 s**
2 CPU: **0.1 s**

Monte Carlo

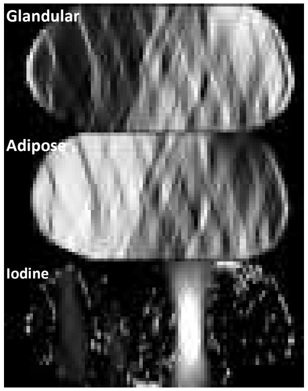
24 CPU: **130 s**

Rodriguez-Ruiz et al, ECR 2019

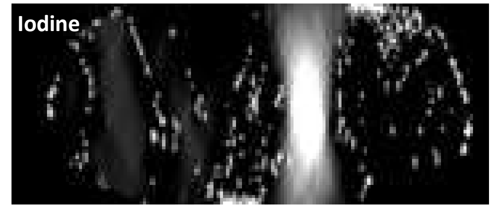


Rodriguez-Ruiz et al, ECR 2019

Limited angle correction in contrast enhanced-DBT



141



2nd pass recon with lesion volume constrain

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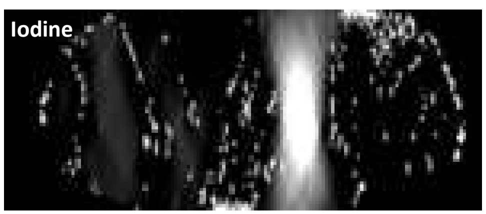

…need to segment the (true) enhancing lesion

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U-net convolutional neural network

Michielsen et al, CT Meeting 2018

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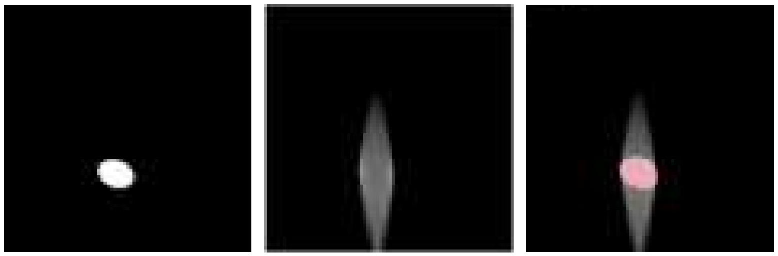
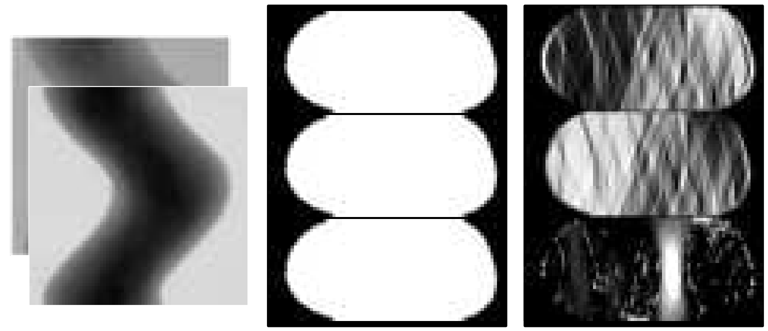
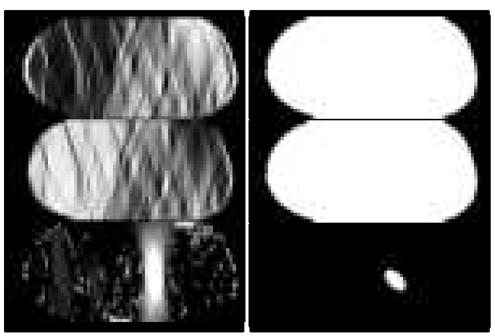


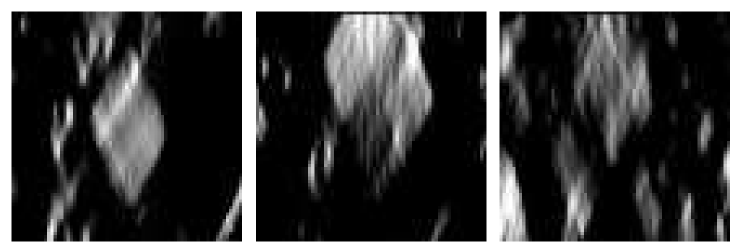
First Pass Reconstruction



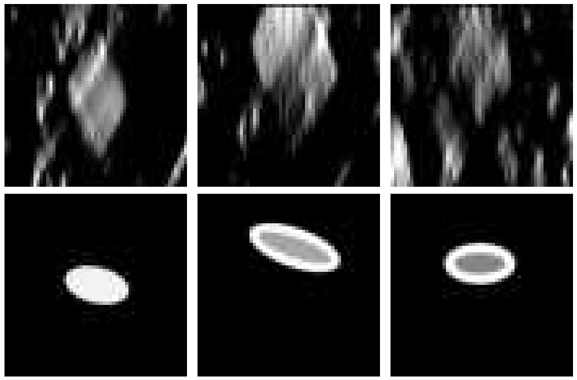
Second Pass Reconstruction



First Pass Reconstruction



Training



Michielsen et al, CT Meeting 2018

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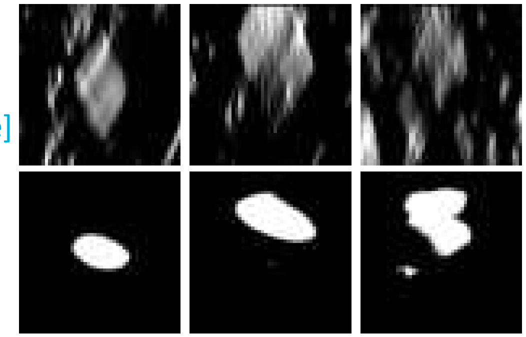
DICE score
[interquartile range]

0.972
[0.936 – 0.984]



Michielsen et al, CT Meeting 2018

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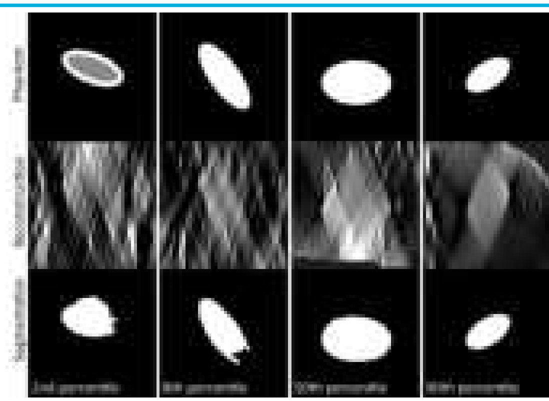

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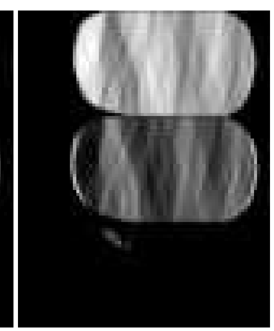
Second Pass Reconstruction



Michielsen et al, CT Meeting 2018

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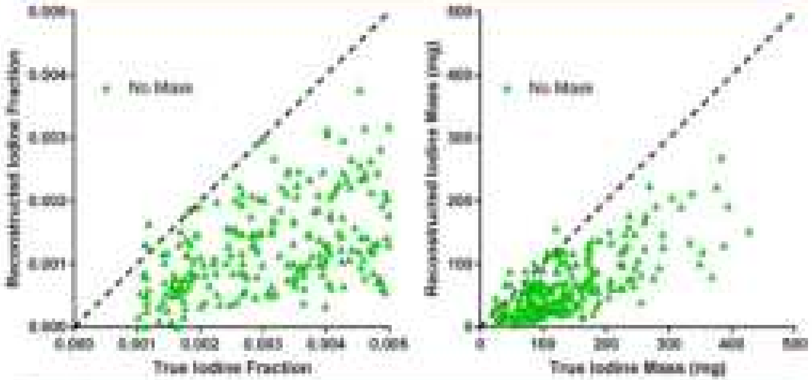

Michielsen et al, CT Meeting 2018

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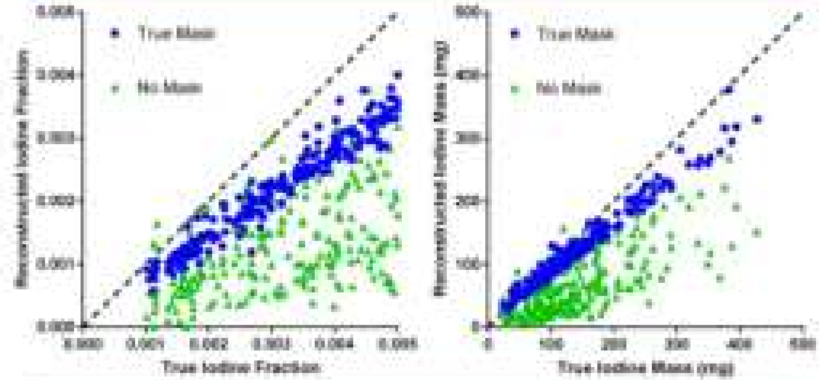

Michielsen et al, CT Meeting 2018

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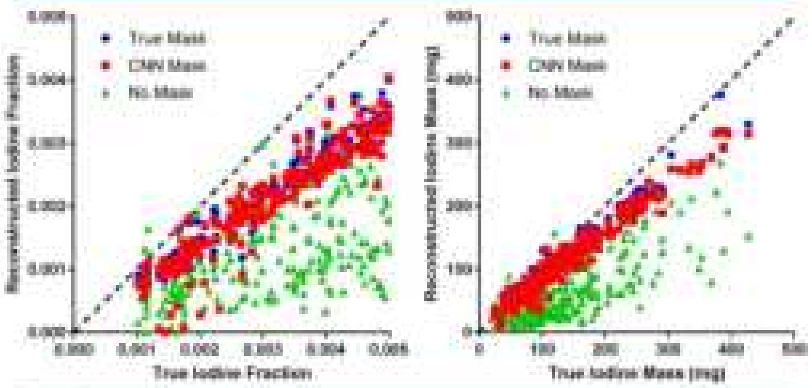

Michielsen et al, CT Meeting 2018

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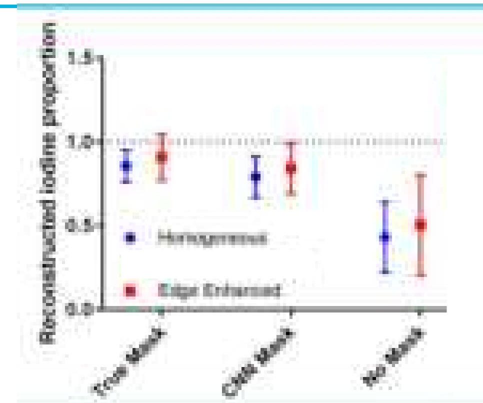

Michielsen et al, CT Meeting 2018

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OF COURSE…

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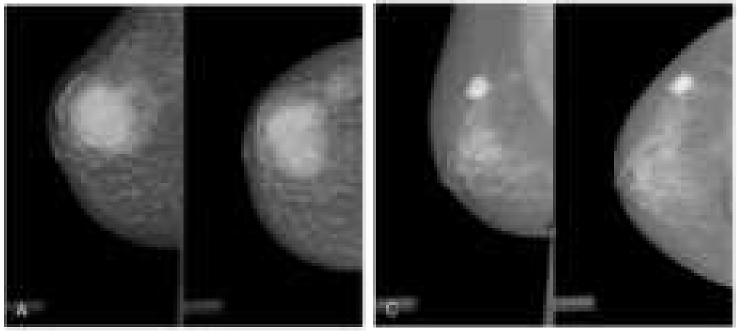

Erhard et al, Investigative Radiology, 2016

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Accurate density estimation and patient-specific dosimetry in DBT

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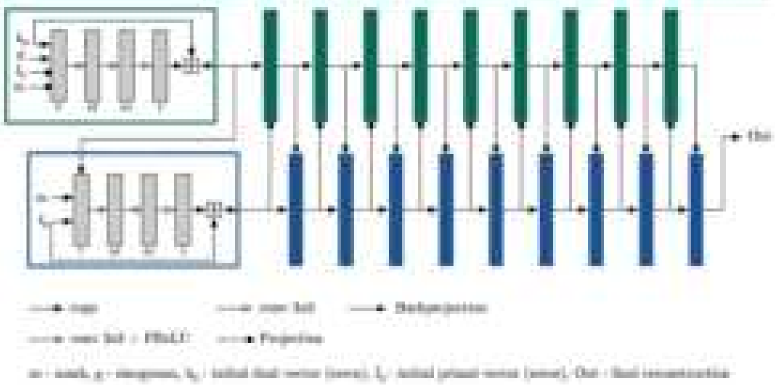

Moriakov et al, IEEE TMI, under review.

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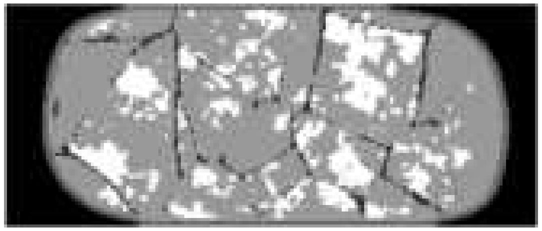

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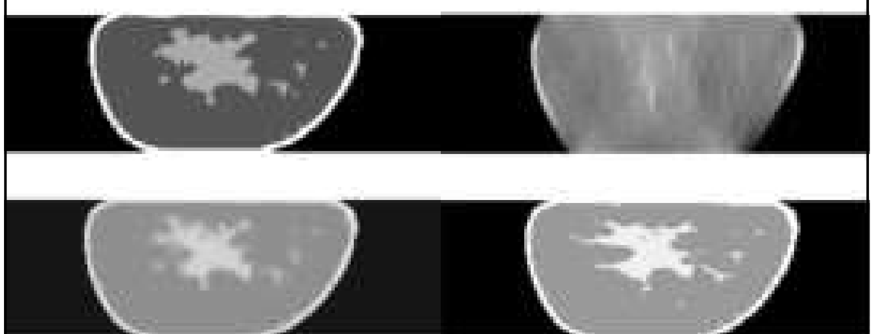
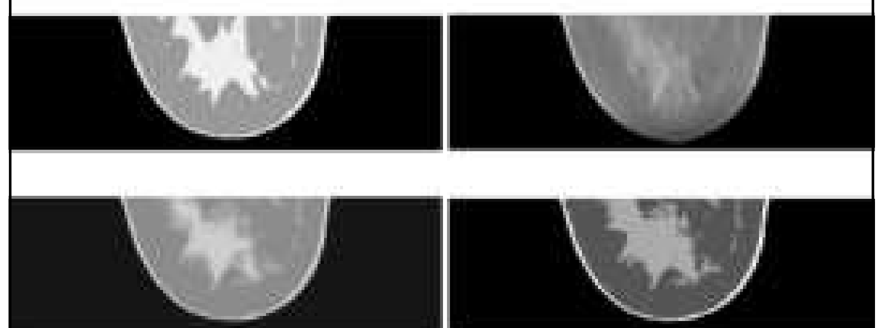
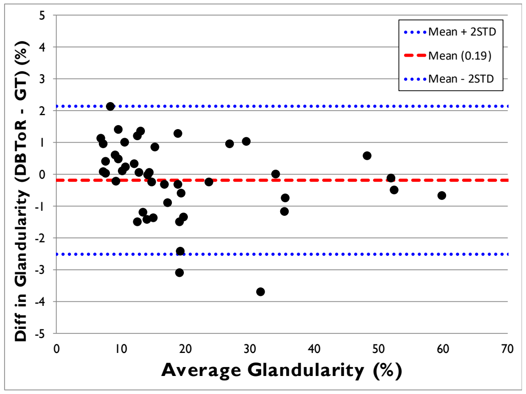
162



163



164



Moriakov et al, IEEE TMI, under review.

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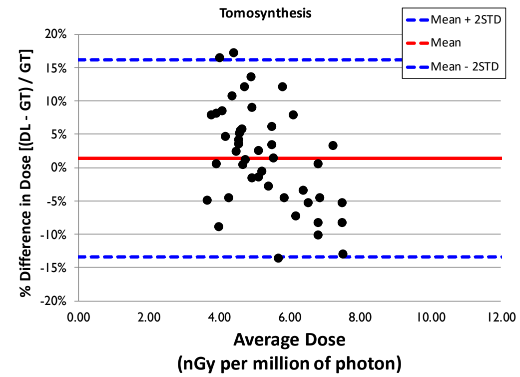

Moriakov et al, IEEE TMI, under review.

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Improved iterative reconstruction

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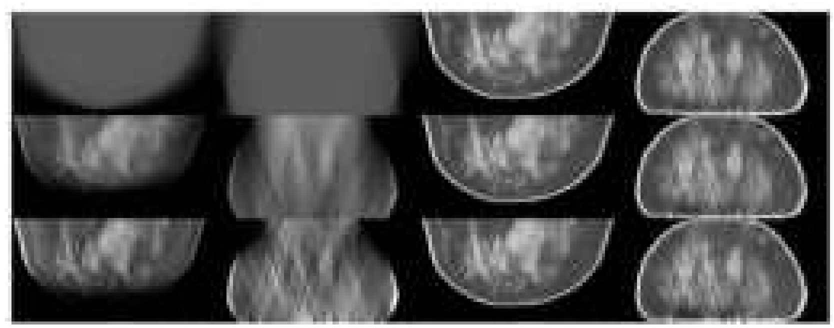

Michielsen et al, CT Meeting 2020, under review.

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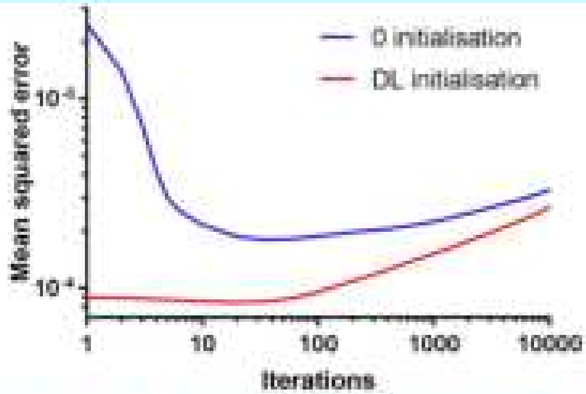

Michielsen et al, CT Meeting 2020, under review.

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...and more:

DL-based radiomics of dedicated breast CT for mass characterization

Automated input parameter selection for dynamic CT perfusion noise filtering

DL-based PET reconstruction with inherent motion correction

Quantization of lung CT perfusion

.....

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...and we are not an AI lab!

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