A novel AI-based paradigm for training radiographers involved in reporting mammography

Brennan PC; Rickard M; Suleiman M; Clerkin N; Gandomkar Z

THE UNIVERSITY OF SYDNEY

DetectedX

Disclosure.

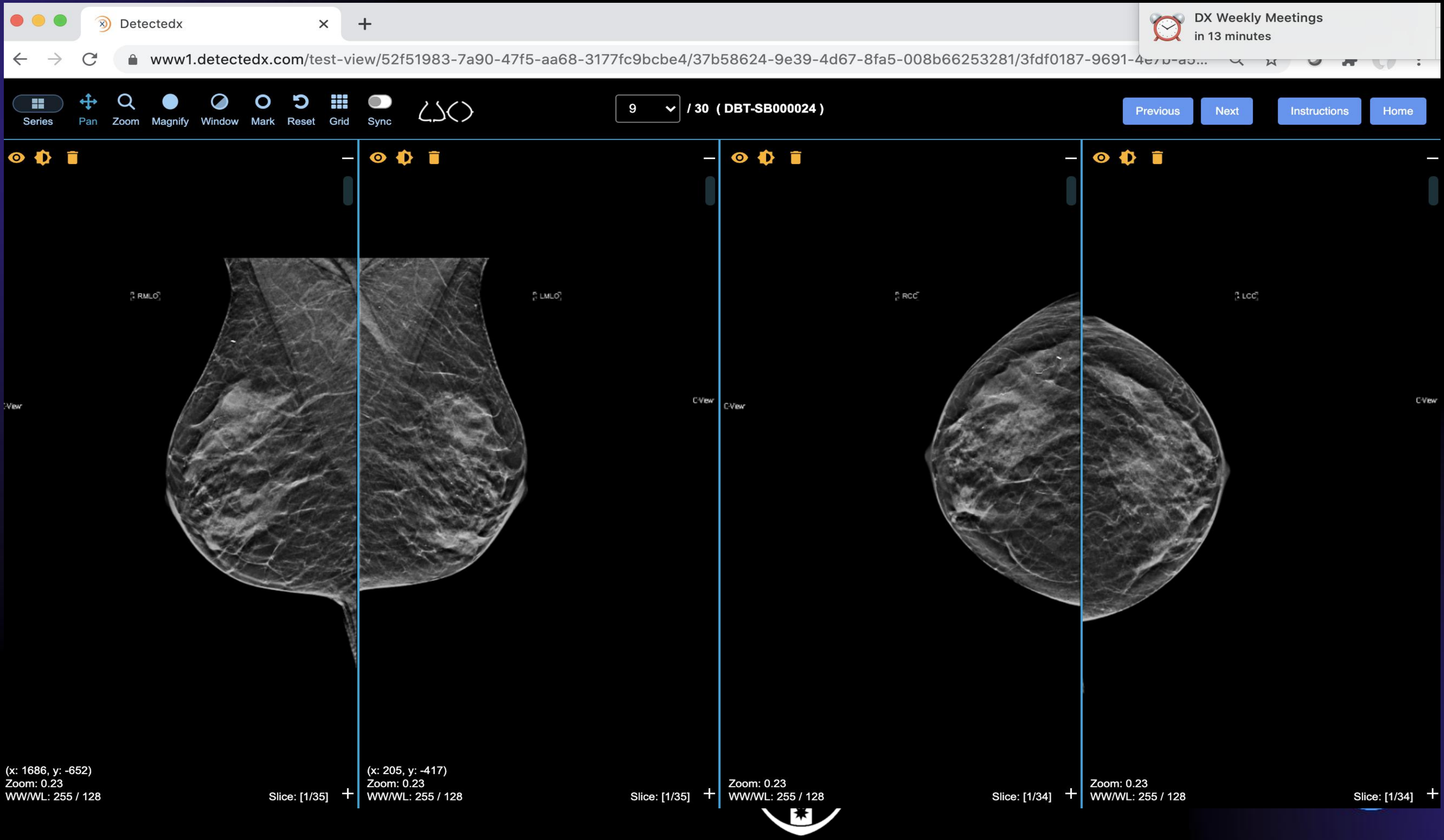
DetectedX

Co-authors




Focus

Education and image-based modules (test sets)


Detectedx
DX Weekly Meetings
in 13 minutes
www1.detectedx.com/test-view/52f51983-7a90-47f5-aa68-3177fc9bcbe4/37b58624-9e39-4d67-8fa5-008b66253281/3fdf0187-9691-4e7b-a5...
Series
Pan
Zoom
Magnify
Window
Mark
Reset
Grid
Sync
9
/ 30 (DBT-SB000024)
Previous
Next
Instructions
Home
RMLO
LMLO
RCC
LCC
C-View
(x: 1686, y: -652)
Zoom: 0.23
WW/WL: 255 / 128
Slice: [1/35]
(x: 205, y: -417)
Zoom: 0.23
WW/WL: 255 / 128
Slice: [1/35]
Zoom: 0.23
WW/WL: 255 / 128
Slice: [1/34]
Zoom: 0.23
WW/WL: 255 / 128
Slice: [1/34]

Results

POSITIVES

True	0
False	0

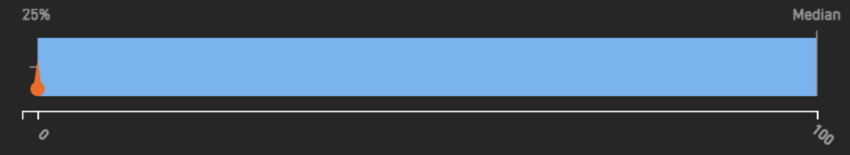
NEGATIVES

True	1
False	1

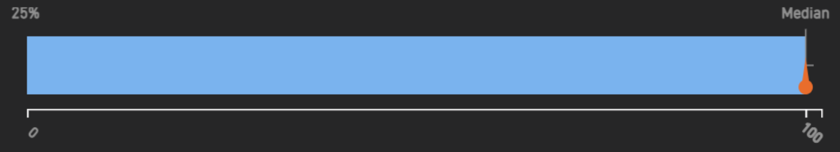
Specificity(%)	100
Sensitivity(%)	0
Lesion sensitivity(%)	0
ROC	0.5
JAFROC	0.5

Download Score | Send Via Email

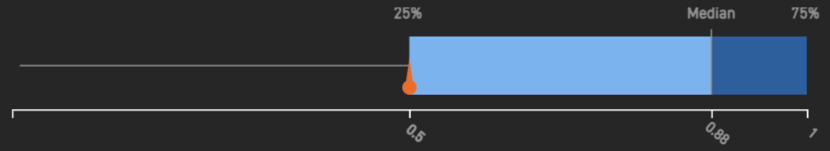
Sensitivity compared to Radiologist



Specificity compared to Radiologist



ROC compared to Radiologist



Certificate of Completion

You must review your answers before receiving your certificate of completion

Certificate Of Completion | Send Via Email

Answers

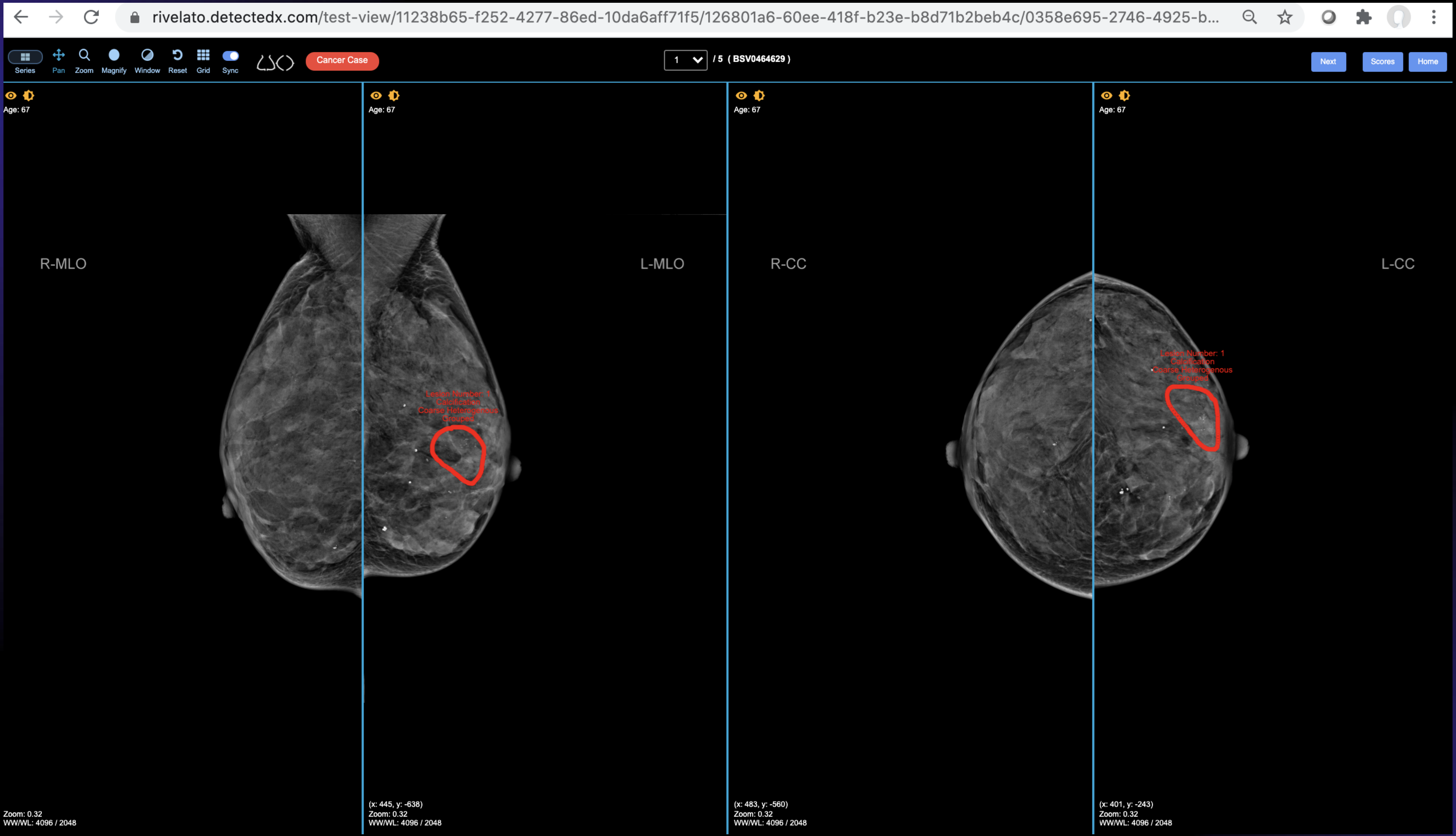
Review your answers alongside our notes of why cases were scored in that way.

Answers

Score Definitions

Click here to find out more about what each of your scores mean.

Definitions



rivelato.detectedx.com/test-view/11238b65-f252-4277-86ed-10da6aff71f5/126801a6-60ee-418f-b23e-b8d71b2beb4c/0358e695-2746-4925-b...
Series
Pan
Zoom
Magnify
Window
Reset
Grid
Sync
Cancer Case
1
/ 5 (BSV0464629)
Next
Scores
Home
Age: 67
R-MLO
Zoom: 0.32
WW/WL: 4096 / 2048
Age: 67
L-MLO
Lesion Number: 1
Calcification
Coarse Heterogenous
Grouped
(x: 445, y: -638)
Zoom: 0.32
WW/WL: 4096 / 2048
Age: 67
R-CC
(x: 483, y: -560)
Zoom: 0.32
WW/WL: 4096 / 2048
Age: 67
L-CC
Lesion Number: 1
Calcification
Coarse Heterogenous
Grouped
(x: 401, y: -243)
Zoom: 0.32
WW/WL: 4096 / 2048

Background: Motivation

Reader	2011	2012 (variation between 2011 and 2012)	2013 (variation between 2011 and 2013)
1	0,65	0.86 (32%)	0.80 (23%)
2	0.48	0.54 (13%)	0.67 (40%)
3	0.51	0.60(18%)	0.68 (33%)
4	0.60	0.61 (2%)	0.71 (18%)
5	0.65	0.75 (15%)	0.80 (23%)
6	0.58	0.74 (28%)	0.75 (29%)
7	0.67	0.89 (33%)	0.98 (46%)
8	0.64	0.86 (34%)	0.93 (45%)
9	0.64	0.83 (30%)	0.94 (47%)
10	0.72	0.88 (22%)	0.98 (36%)
11	0.50	0.70 (40%)	0.73 (46%)
12	0.68	0.78 (15%)	0.83 (22%)
13	0.57	0.70 (23%)	0.82 (44%)
14	0.61	0.80 (31%)	0.79 (30%)
Mean variation		24.0%	34.4%

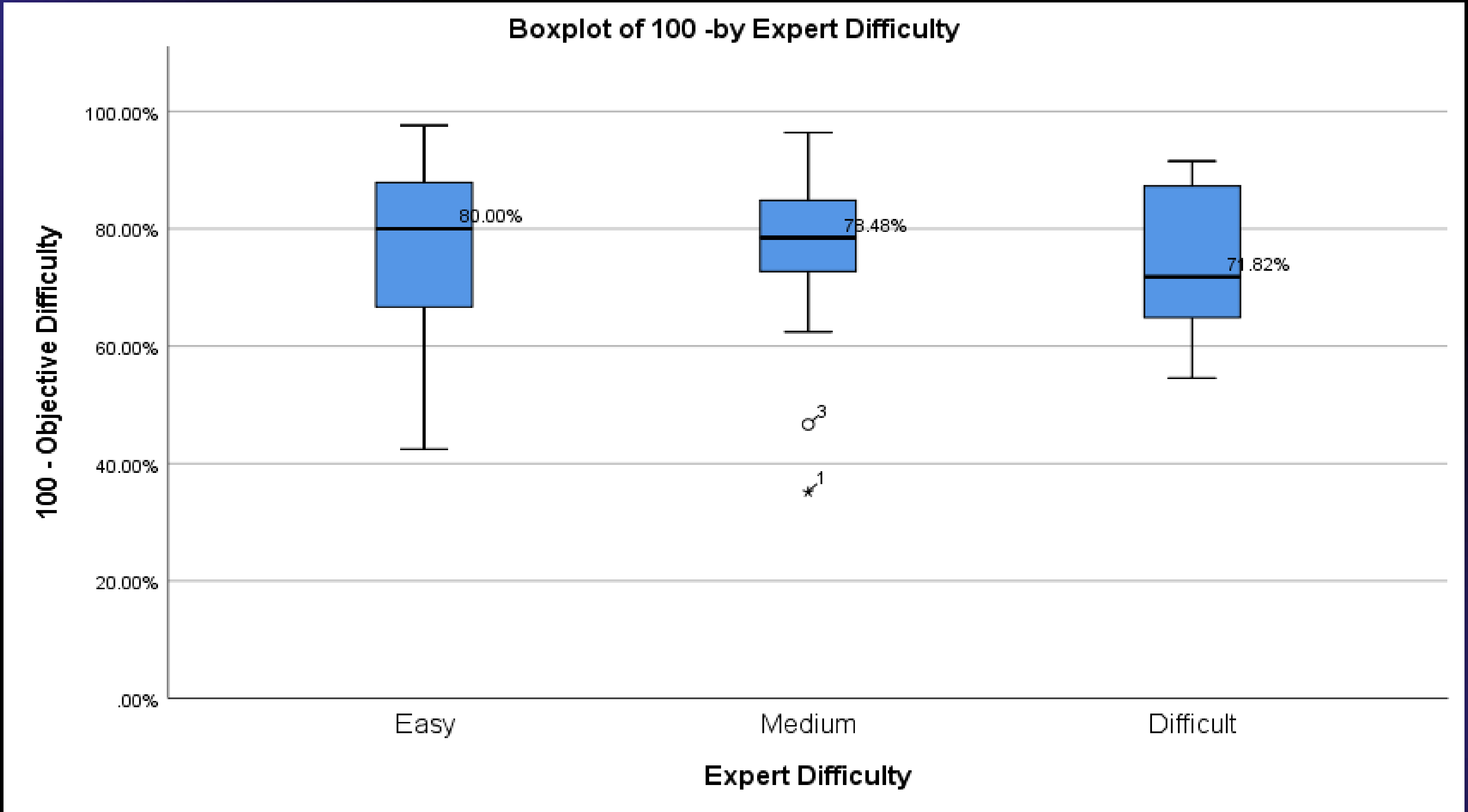
Background: Motivation

- However.....
- One-size-fits-all: improvement levels can be below 10%
- Artificial Intelligence (AI)?

Background: Motivation

It is about predicting difficulty and understanding which learners are struggling.

Background: Relying on experts to determine case difficulty



Purpose

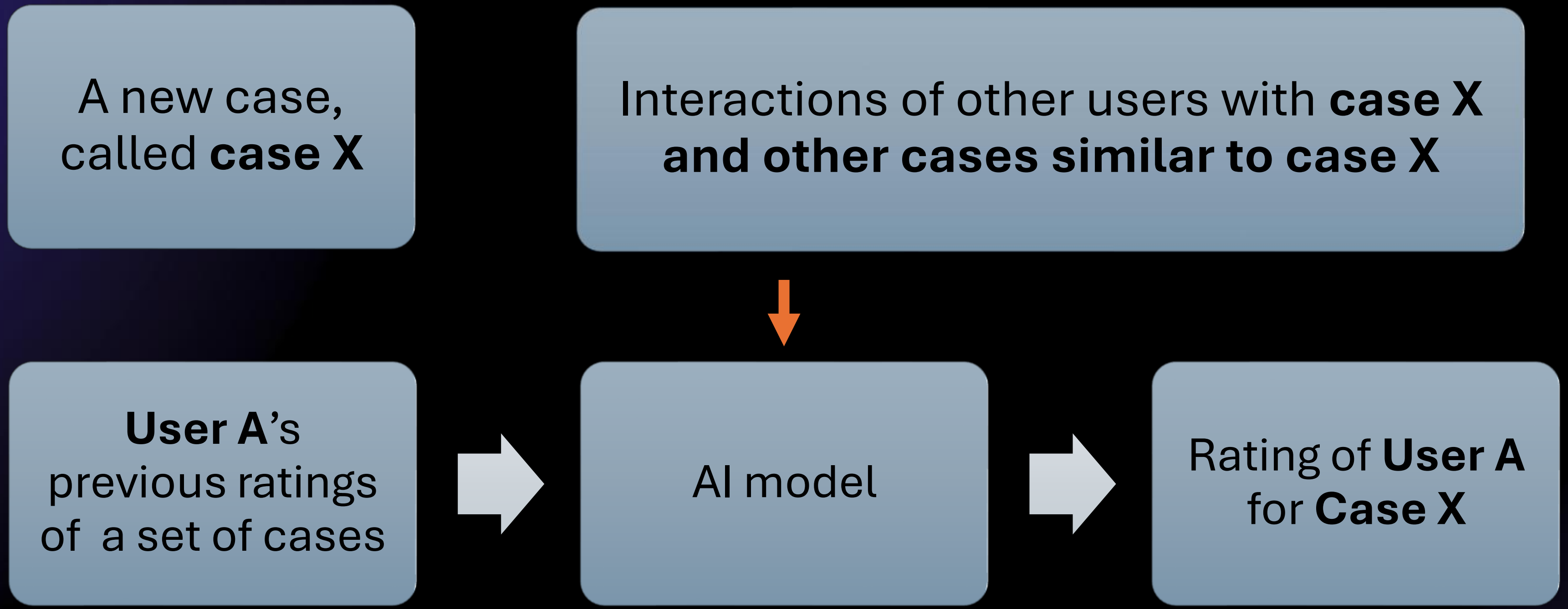
Can we personalise self-assessment modules for reporting radiographers.

Methods

Methods

(there are actually three scenarios)

Methods


A new case, called **case X**
Interactions of other users with **case X and other cases similar to case X**
User A's previous ratings of a set of cases
AI model
Rating of **User A** for **Case X**

Methods

- We used "Funk's SVD": Matrix Factorization technique
- Originally proposed for "Netflix challenge"
- 100M ratings (from 1 to 5) of 17K movies by 500K users.
- Arrives as a triplet of numbers: (User, Movie, Rating).
- Problem: User A, Movie X not in the database

So let us benefit from other domains:

- Netflix: User A; Movie X
- Reporting radiographers: Learner A; Case X

Methods

- Twenty-four reporting radiographers
- 60 mammographic cases: 20 cancers, 40 normals
- 1–5 probability-of-abnormality score

Methods

- A difficult ***cancer*** case is a case, rated 2 or less
- A difficult ***normal*** case is a case rated 3 or more.

Methods: defining difficulty

- Leave-one-out cross-validation to evaluate performance
- A baseline model based on average ratings

Results

Results (cancers)

The AUC for detecting difficult ***cancer*** cases:

0.78

Results (normals)

The AUC for detecting difficult ***normal*** cases:

0.84

The proposed model vs Baseline

	Baseline	Proposed Model
Cancer	0.66	0.78
Normal	0.71	0.84

The idea can be extended to other *populations*....

- Eg. 260 radiologists, 12 breast physicians, and 207 radiology trainees

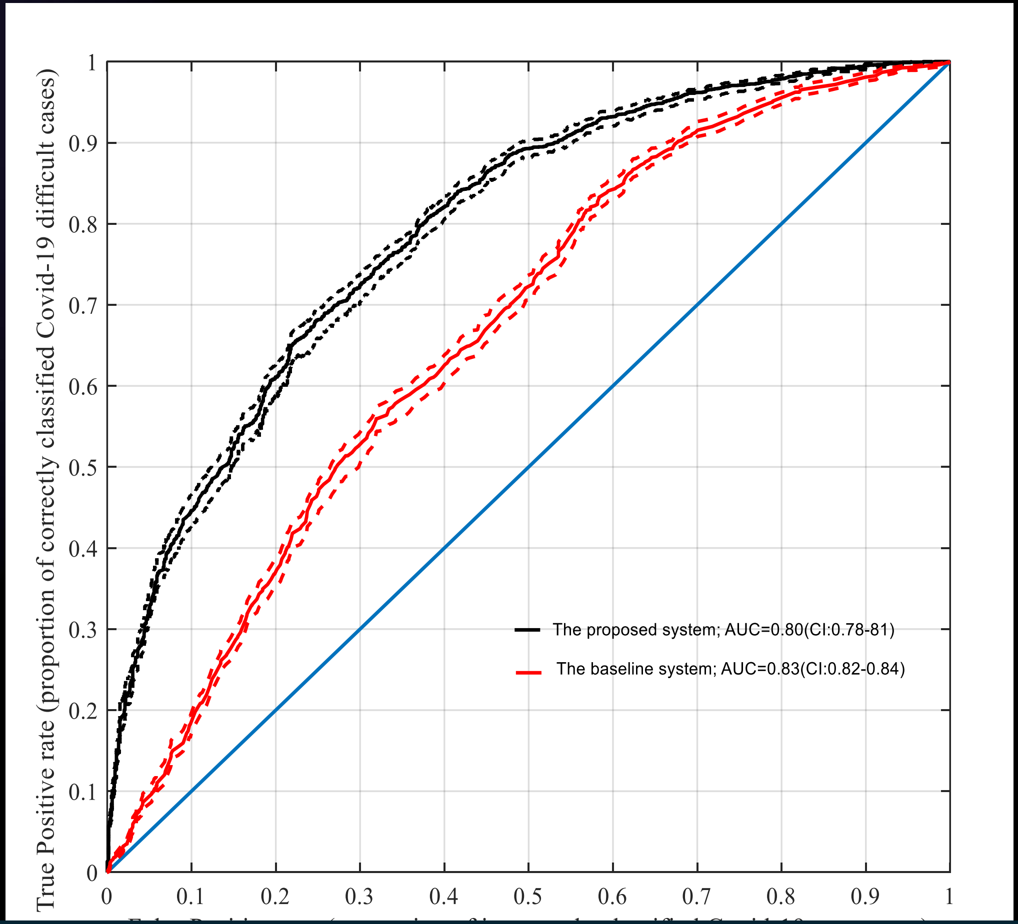
The proposed model vs Baseline

	Baseline	Proposed Model
Cancer	0.73	0.87
Normal	0.67	0.70

The idea can be extended to other *diseases*...

Eg. COVID-19

Eg. Covid 19


True Positive rate (proportion of correctly classified Covid-19 difficult cases)
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
The proposed system; AUC=0.80(CI:0.78-81)
The baseline system; AUC=0.83(CI:0.82-0.84)

Overall conclusions

- Initial results are promising for predicting difficulty for:
    - Existing user
    - New User
    - New image
- Being implemented (Data, data, data)
- Implications beyond mammography (and beyond radiography/medical imaging)

Recent published works

- Existing user
- New user
- New case

Home > Artificial Intelligence in Medicine > Reference work entry

Optimizing Radiologic Detection of COVID-19

Test Set Technologies and Artificial Intelligence

Reference work entry | First Online: 18 February 2022

pp 511–519 | Cite this reference work entry

Access provided by University of Sydney

Z. Gandomkar, P. C. Brennan & M. E. Suleiman

Recent published works

- Existing user
- **New user**
- New case

Breast Cancer (2022) 29:589–598
https://doi.org/10.1007/s12282-022-01335-3

ORIGINAL ARTICLE

Check for updates

A machine learning model based on readers' characteristics to predict their performances in reading screening mammograms

Ziba Gandomkar[1] · Sarah J. Lewis[1] · Tong Li[1] · Ernest U. Ekpo[1] · Patrick C. Brennan[1]

Received: 28 June 2021 / Accepted: 20 January 2022 / Published online: 5 February 2022

Recent published works

- Existing user
- New user
- New case

BJR, 2025, 98, 75–88
https://doi.org/10.1093/bjr/tqae195
Advance access publication: 9 October 2024
Research Article

British Institute of Radiology
OXFORD

Radiomic analysis of cohort-specific diagnostic errors in reading dense mammograms using artificial intelligence

Xuetong Tao, PhD*,[1], Ziba Gandomkar, PhD[1], Tong Li, PhD[2,3], Patrick C. Brennan, PhD[1], Warren M. Reed, PhD[1]

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Journal of Digital Imaging (2023) 36:1541–1552
https://doi.org/10.1007/s10278-023-00836-7

Global Radiomic Features from Mammography for Predicting Difficult-To-Interpret Normal Cases

Somphone Siviengphanom[1] · Ziba Gandomkar[1] · Sarah J. Lewis[1] · Patrick C. Brennan[1]

Received: 28 November 2022 / Revised: 5 April 2023 / Accepted: 13 April 2023 / Published online: 30 May 2023

Journal of Imaging Informatics in Medicine
https://doi.org/10.1007/s10278-024-01291-8

ORIGINAL PAPER

A Machine Learning Model Based on Global Mammographic Radiomic Features Can Predict Which Normal Mammographic Cases Radiology Trainees Find Most Difficult

Somphone Siviengphanom[1] · Patrick C. Brennan[1] · Sarah J. Lewis[1,2] · Phuong Dung Trieu[1] · Ziba Gandomkar[1]

Received: 1 June 2024 / Revised: 28 September 2024 / Accepted: 30 September 2024

Journal of Personalized Medicine
MDPI

Article

Using Radiomics-Based Machine Learning to Create Targeted Test Sets to Improve Specific Mammography Reader Cohort Performance: A Feasibility Study

Xuetong Tao [1,*], Ziba Gandomkar [1], Tong Li [2,3], Patrick C. Brennan [1] and Warren Reed [1]

3 October 2024

Optimizing mammography interpretation education: leveraging deep learning for cohort-specific error detection to enhance radiologist training

Xuetong Tao, Warren M. Reed, Tong Li, Patrick C. Brennan, Ziba Gandomkar

Author Affiliations +

Journal of Medical Imaging, Vol. 11, Issue 5, 055502 (October 2024).
https://doi.org/10.1117/1.JMI.11.5.055502

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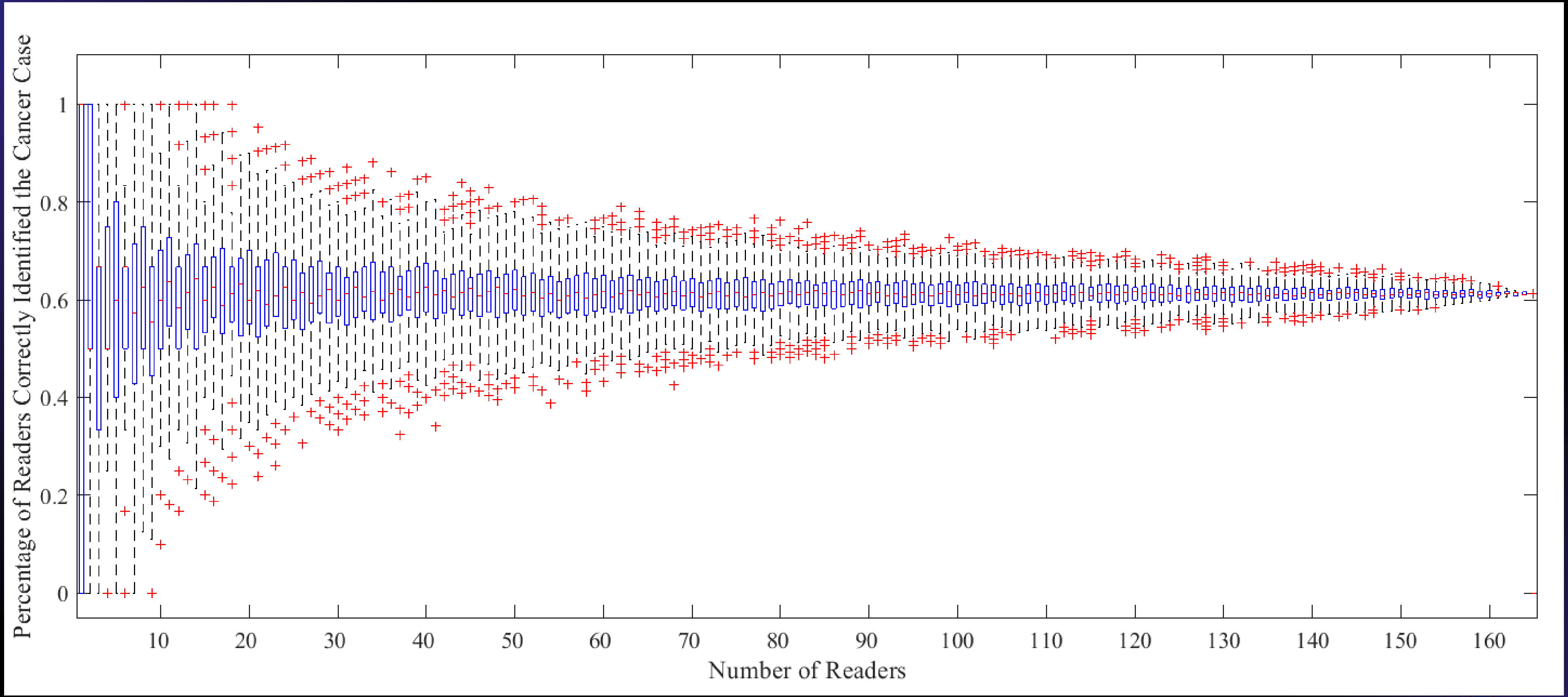
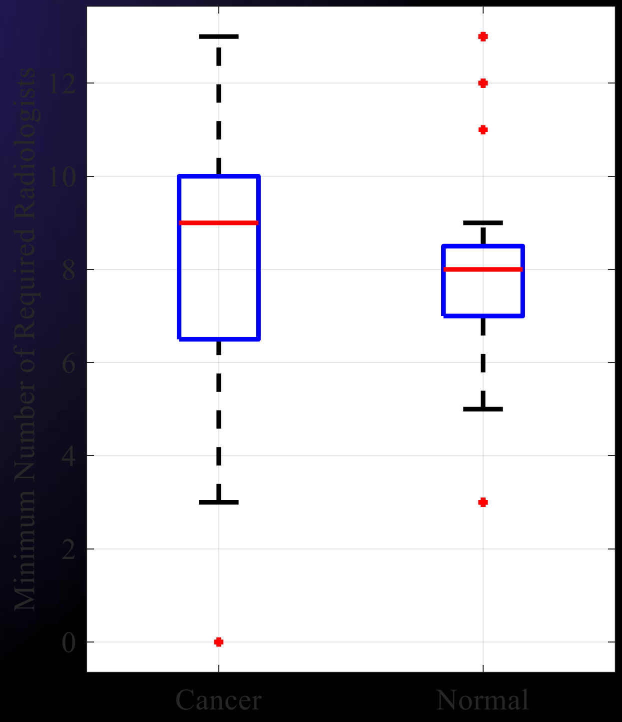


Percentage of Readers Correctly Identified the Cancer Case
0
0.2
0.4
0.6
0.8
1
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
Number of Readers

DetectedX


Minimum Number of Required Radiologists
0
2
4
6
8
10
12
Cancer
Normal
DetectedX