Scandinavian Japanese Radiological Society
Keynote Lecture, Munkebjerg Hotel, Velje, Denmark
Monday, September 6th , 2010, 10:00-10:30 am

Achievements and Challenges of Computer-Aided Diagnosis in Radiology

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Topics and the Number of Papers presented at RSNA* from 2000 to 2009

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
CAD	55	86	134	181	161	165	167	200	227	132+
Dig Mamm	12	15	20	25	27	22	34	44	31	-
Lng CancSc	6	12	19	21	17	7	18	10	10	-
CR/DR/FPD	14	20	14	25	18	16	27	24	9	-

*Radiological Society of North America

Number of CAD Papers Presented at RSNA 2003-2009

	2003	2004	2005	2006	2007	2008	2009
Chest	94	70	48	62	72	73	45
Breast	37	48	49	47	39	51	42
Colon	17	15	30	25	32	24	14
Brain	10	9	17	12	13	20	3
Liver	9	9	9	8	8	22	8
Skeletal	9	8	5	7	11	6	4
Vascular etc*	15	2	7	6	17	31	16
Total	181	161	165	167	200	227	132+

*Cardiac, Prostate, Pediatric, Dental, PACS

What is computer-aided diagnosis (CAD) ?

Diagnosis made by a radiologist who takes into account the computer output as a “second opinion”

What can we expect from a high computer performance?

(1) A high computer performance does not necessarily provide a high CAD performance.

(2) A low computer performance can provide a high CAD performance.

What kinds of computer performance are useful to CAD?

(1) Not useful if obvious lesions are easily detectable by radiologists without computer.

(2) Not useful if subtle lesions are not actionable even with correct computer results.

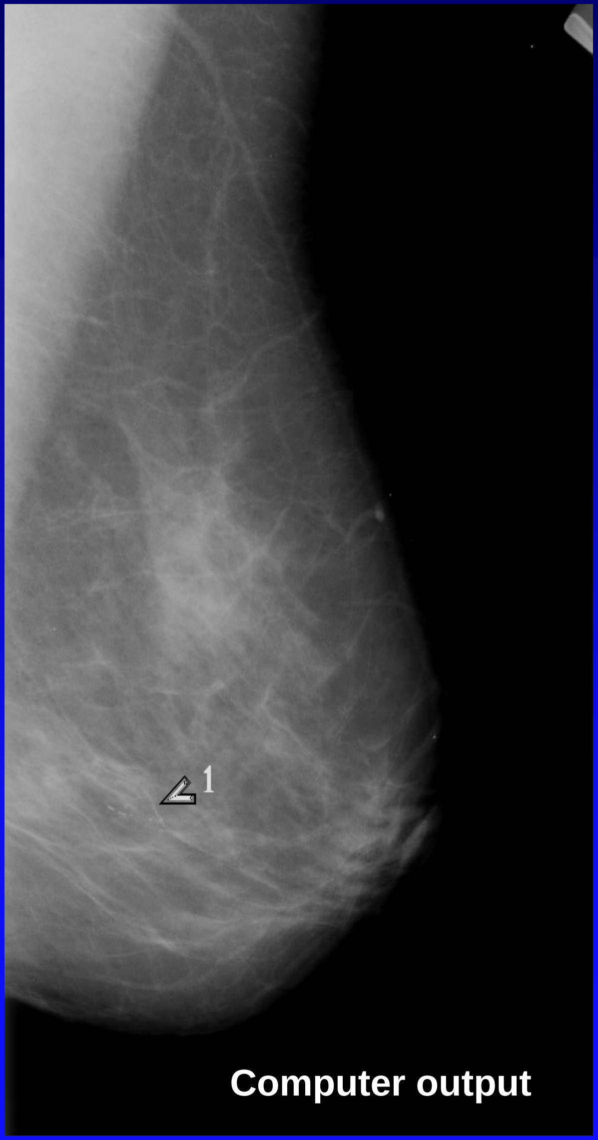
(3) Useful if radiologists can recognize potentially "missed" lesions with computer results.

Summary on CAD

(1) Serious investigations began around 1983
(2) ROC analysis providing evidence for improved radiologists' performance with CAD
(3) Commercialization and FDA approval on
R2 mammo CAD system in 1998,
Riverain (Deus) chest CAD system in 2001,
(4) Approval of reimbursement in 2003
(5) 20% gain in breast cancer detection rate
with CAD in a prospective study by Freer et al

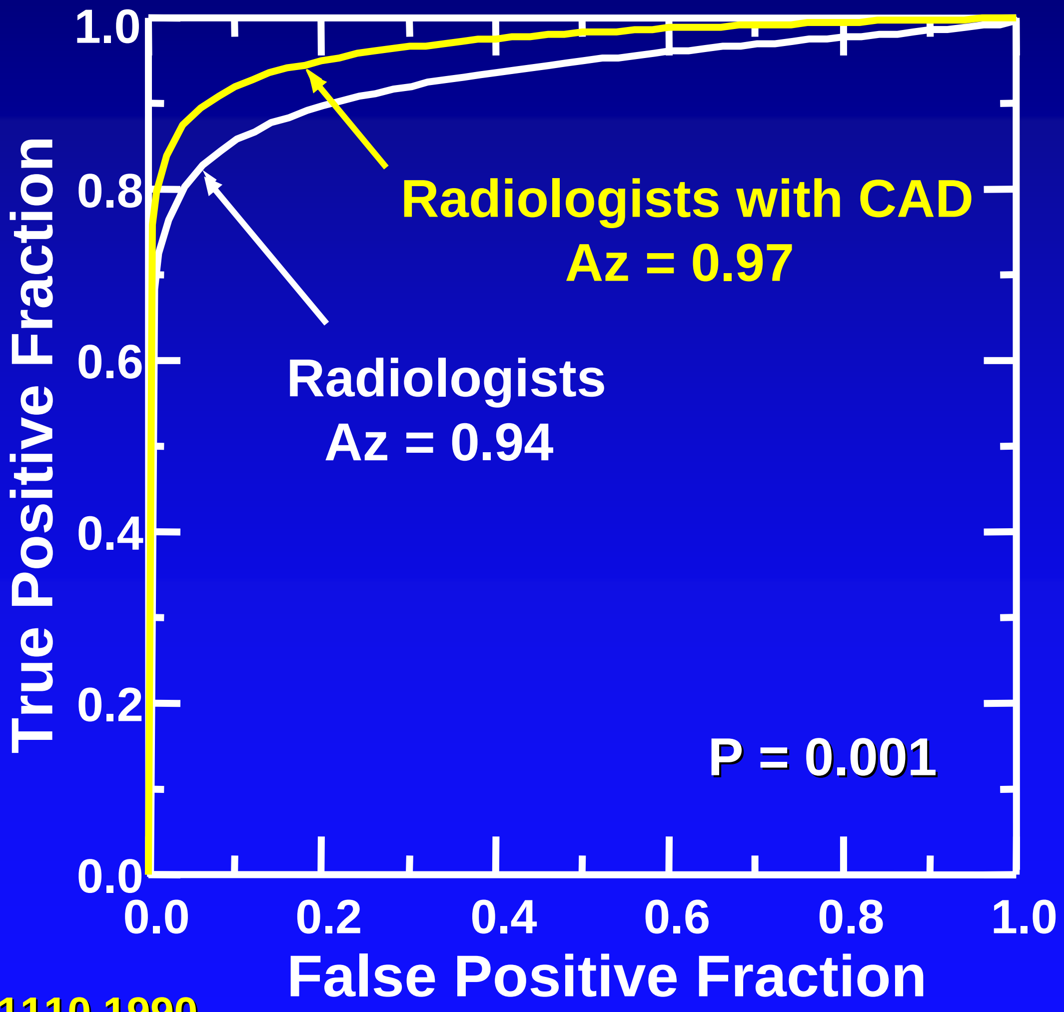
First CAD System at University of Chicago (1994)

Computerized Detection of Clustered Microcalcifications on Mammogram



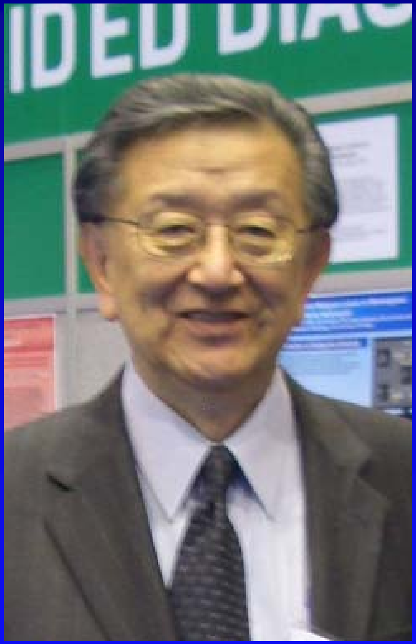
First Scientific Evidence for the Benefits of CAD in the Detection of Microcalcifications

Heang-Ping Chan, PhD
Univ of Michigan

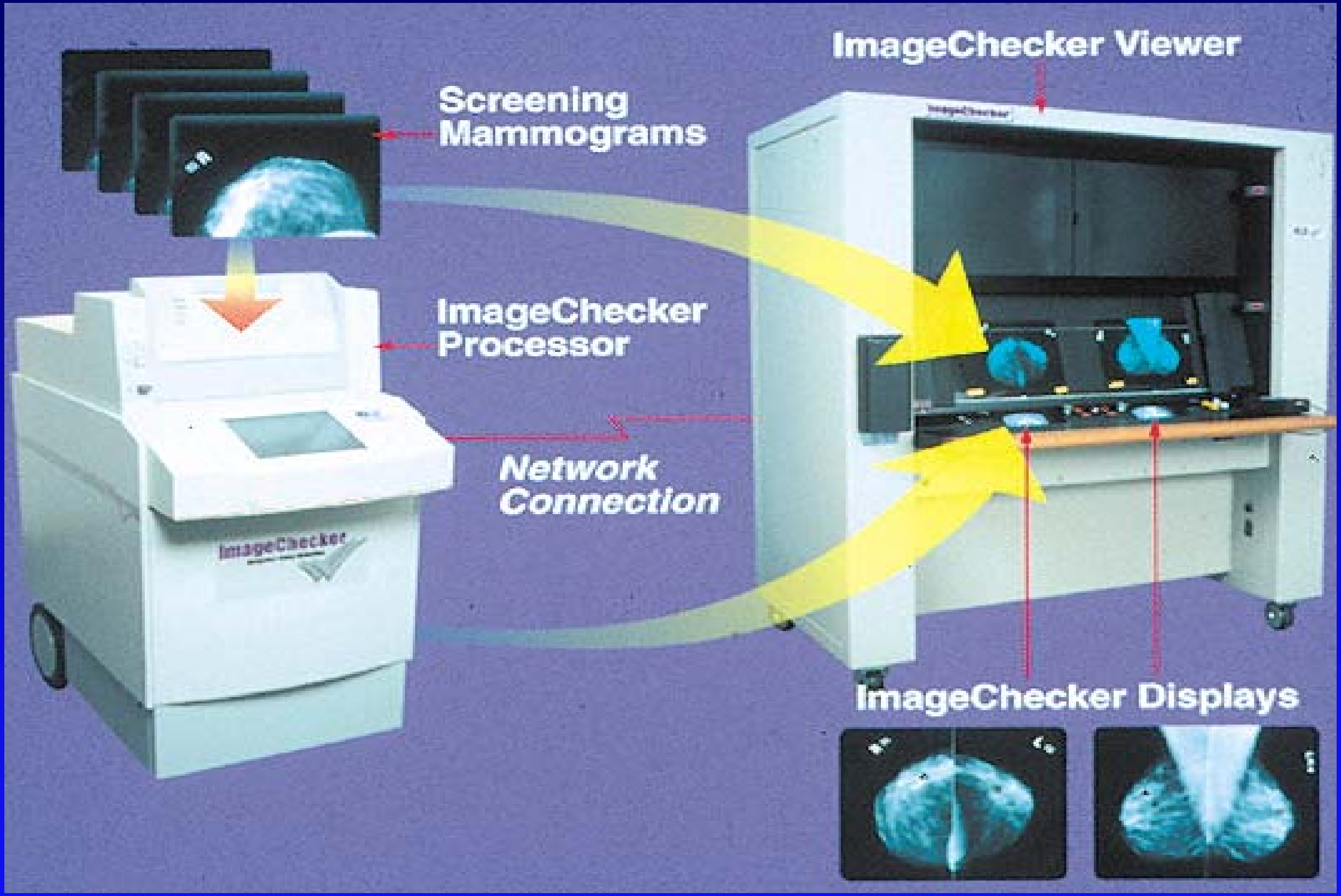


H.P. Chan et al. Inv Rad 25: 1102-1110,1990

ImageChecker (1998)

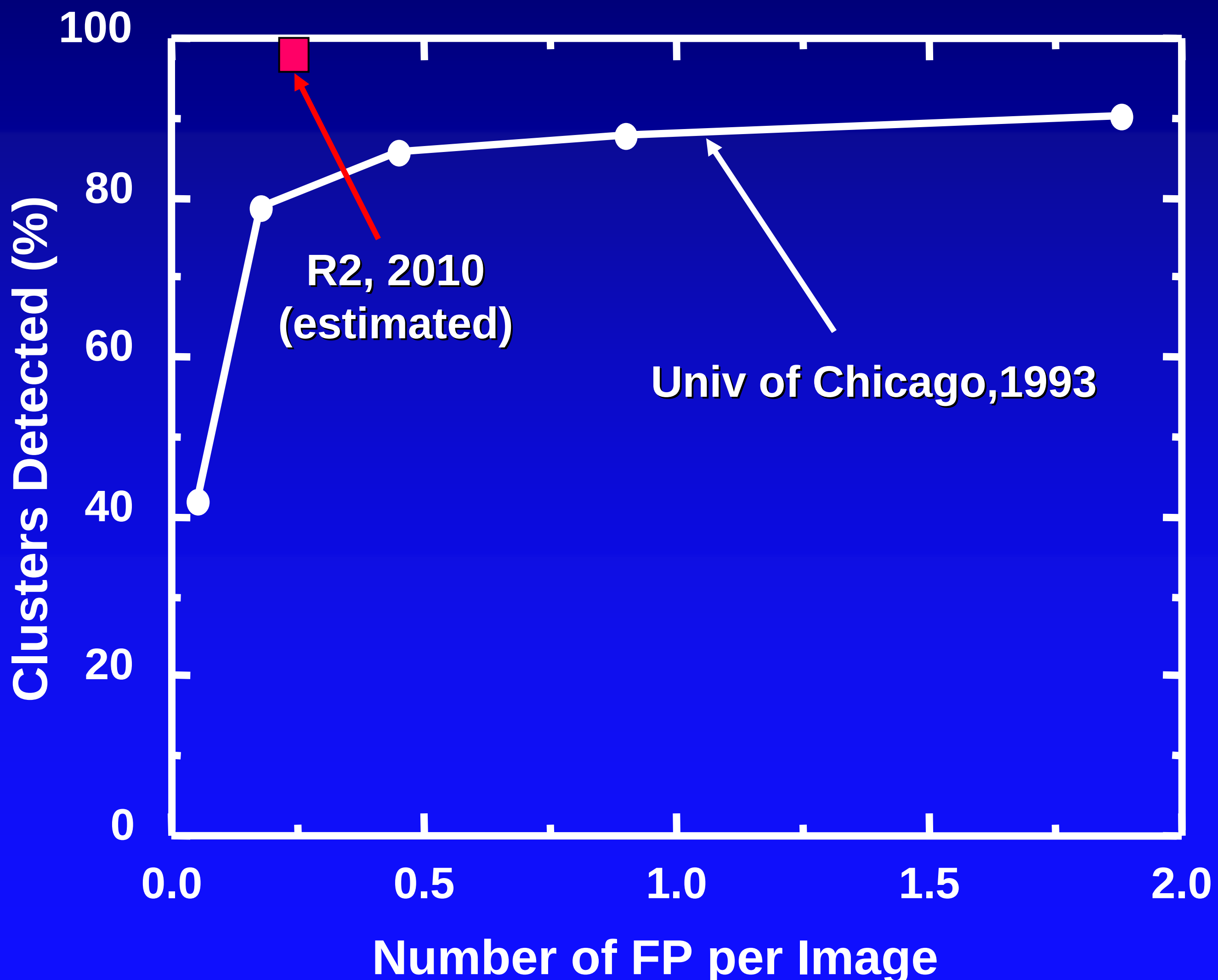


Bob S. P. Wang
Founder, R2 Technology
(1993)



R2 Technology / Hologic

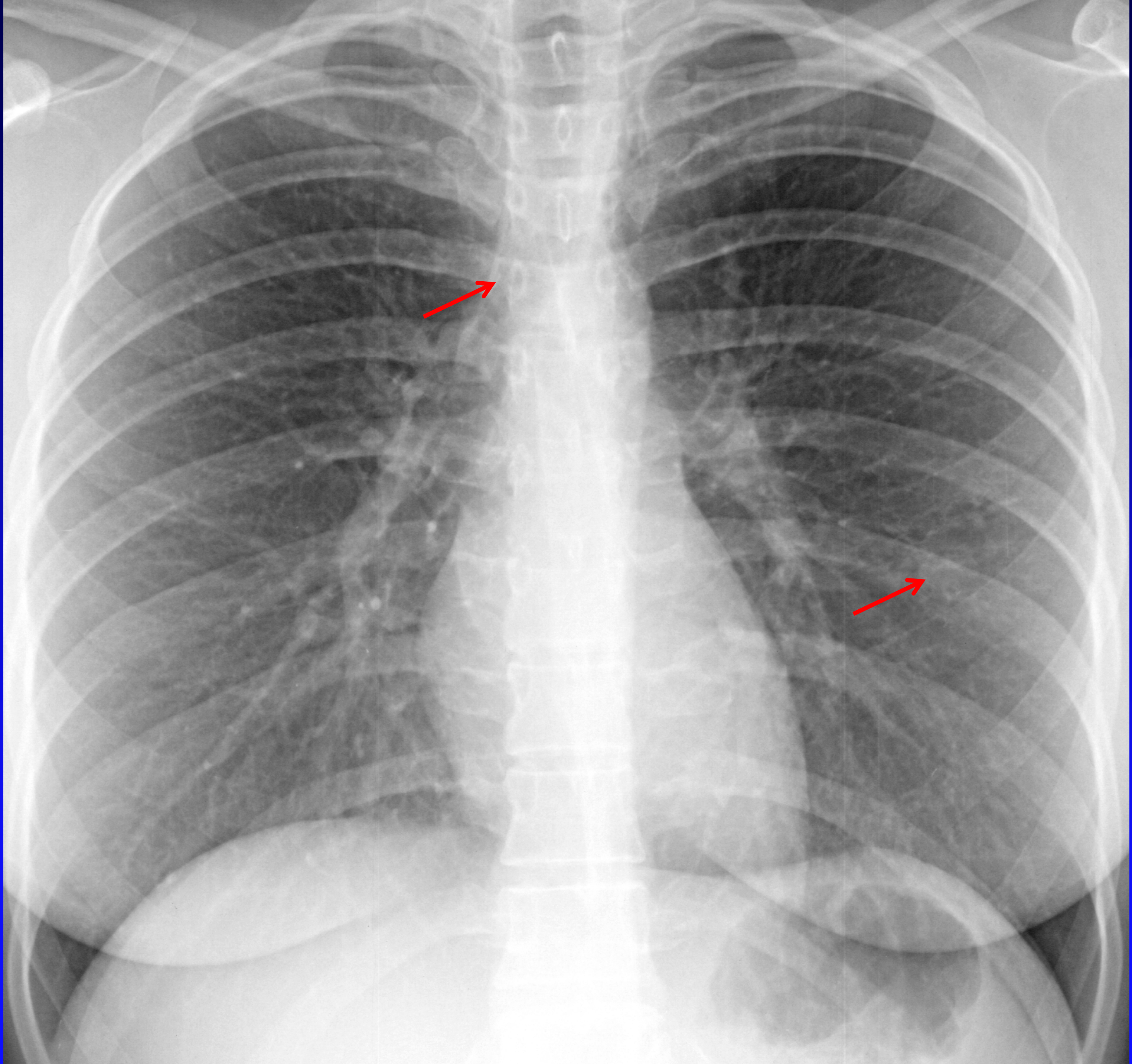
Automated Computerized Detection of Clustered Microcalcifications



Prospective Clinical Studies for CAD in Screening Mammography

			No of cases	Gain in cancer detection rate	Increase in recall rate
Freer et al.	Radiology	2001	12,860	19.5%	18.8%
Gur et al.	J of NCI	2004	115,571	1.7%	0.1%
Birdwell et al.	Radiol.	2005	8,682	7.4%	7.6%
Cupples et al.*	AJR	2005	27,274	16.1%	8.1%
Morton et al.	Radiol.	2006	18,096	7.6%	10.8%
Gromet	AJR	2008	231,221	11.0%	4.0%

* 164% increase in detection of small (<1.0cm) invasive cancer
Mean age of patients was 5.3 years younger at time of detection

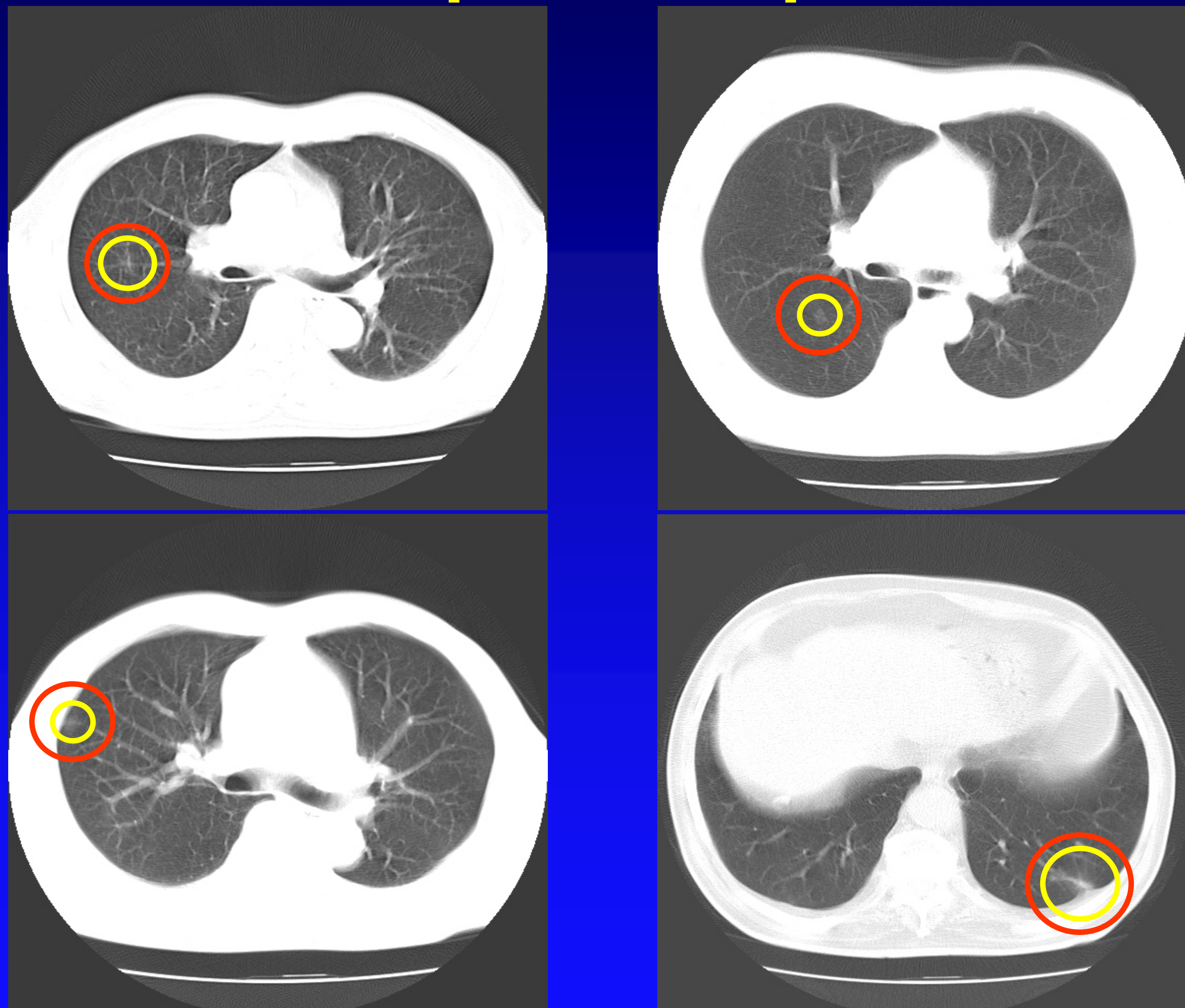


RapidScreen System (2001)

Riverain Medical (Deus Technology)

Missed Lung Cancers in LDCT for Screening

Computer output



F. Li et al. Radiology 225: 673-683, 2002 Armato et al. Radiology 225: 695-700, 2002

CAD for Classification :
Effect of the Likelihood of Malignancy on Distinction between Benign and Malignant Nodules on Thin-Section CT

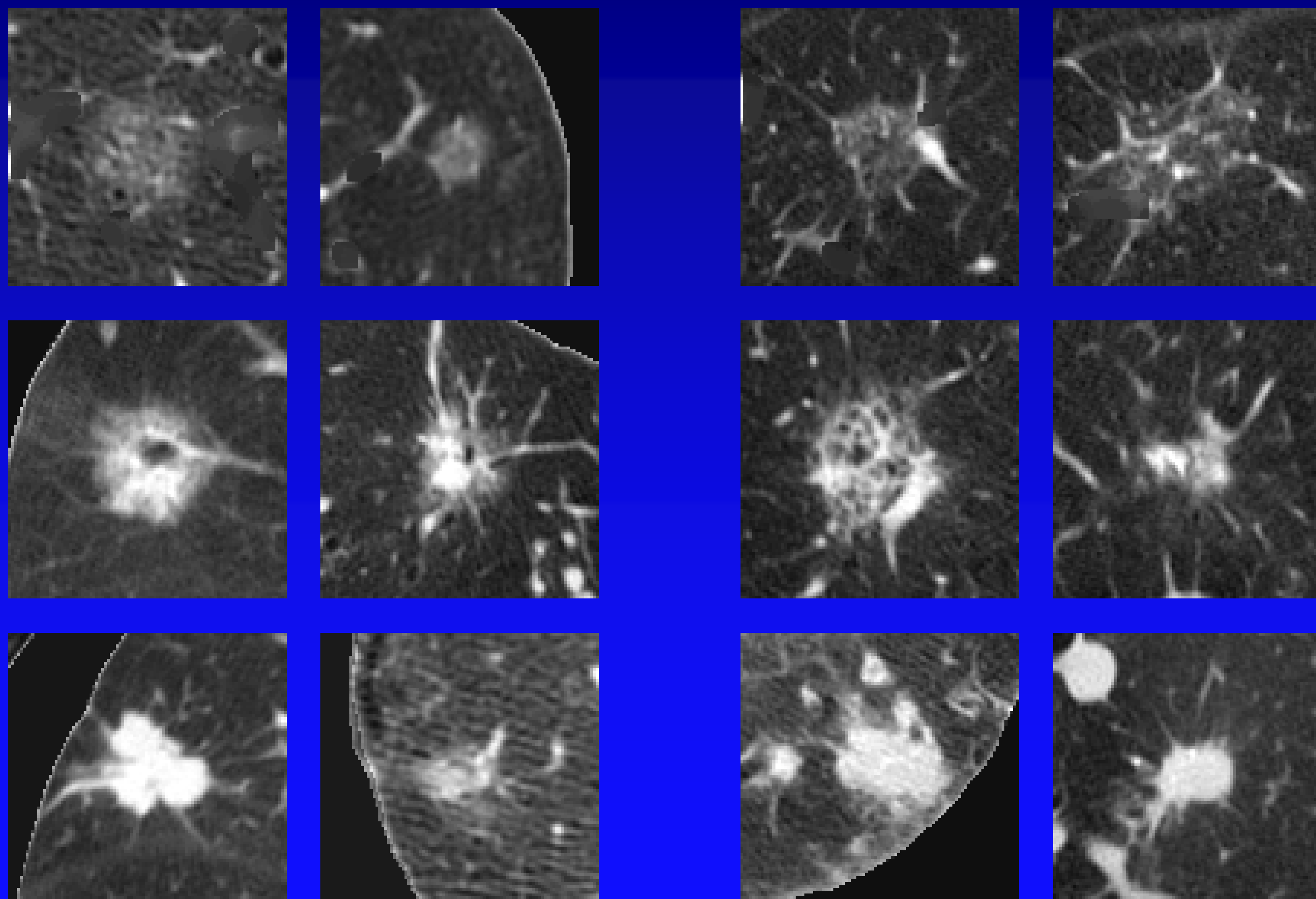
Malignant and Benign Nodules with GGO, mixed GGO, and Solid Opacity

Malignant | Benign

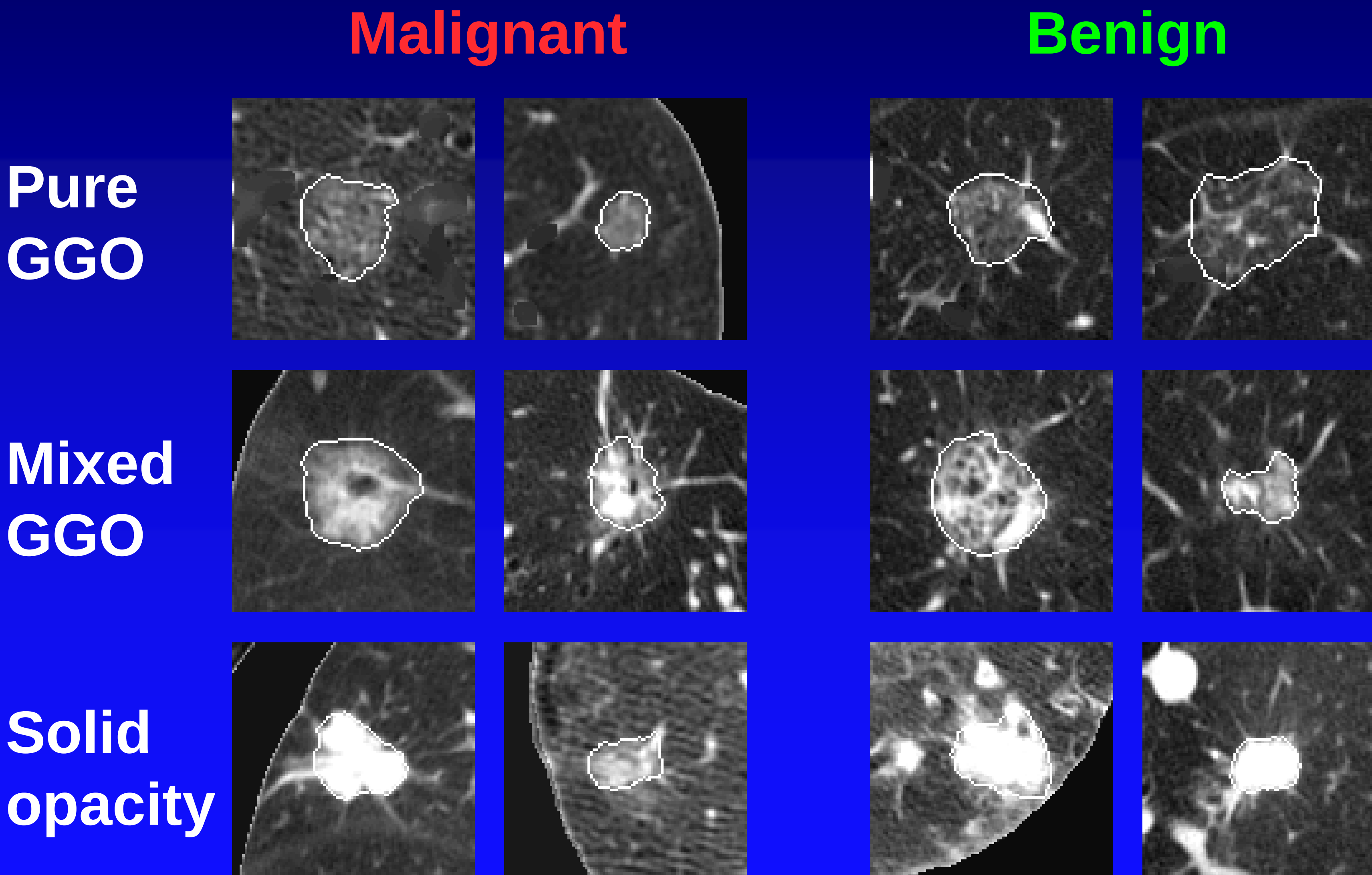
Pure GGO

Mixed GGO

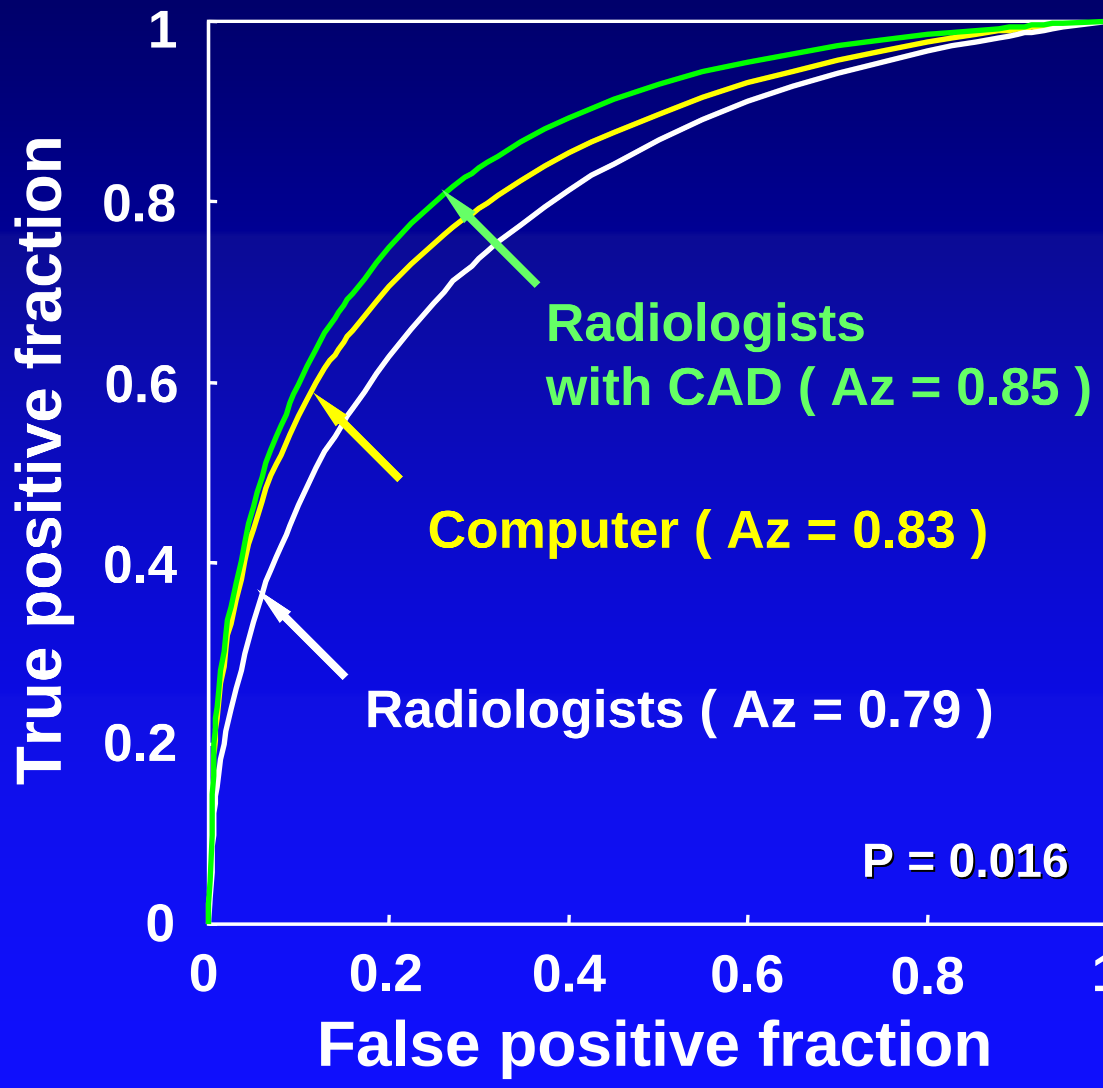
Solid opacity



Extracted Nodule Regions by Automated Nodule Segmentation



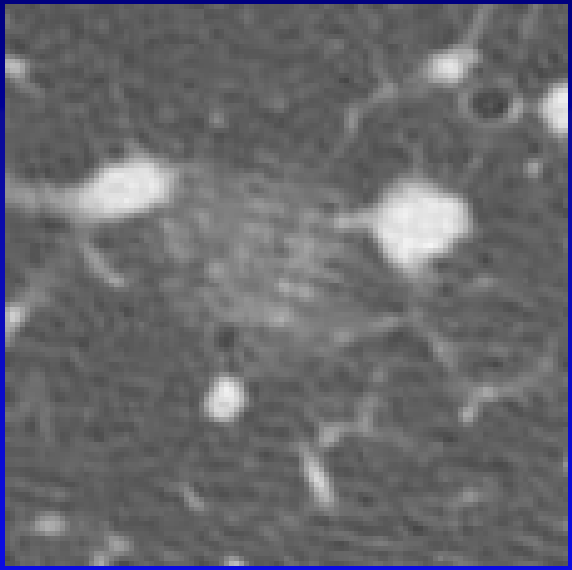
ROC Curves for 16 Radiologists without and with CAD Scheme



F. Li et al. AJR 183: 1209-1215, 2004

Difficult Cases, but Correct Computer Output :

Beneficial Changes in Radiologists' Ratings due to CAD



Malignant nodule

Initial rating (0-1.0): 0.49
Computer output: 0.97
2nd rating: 0.67

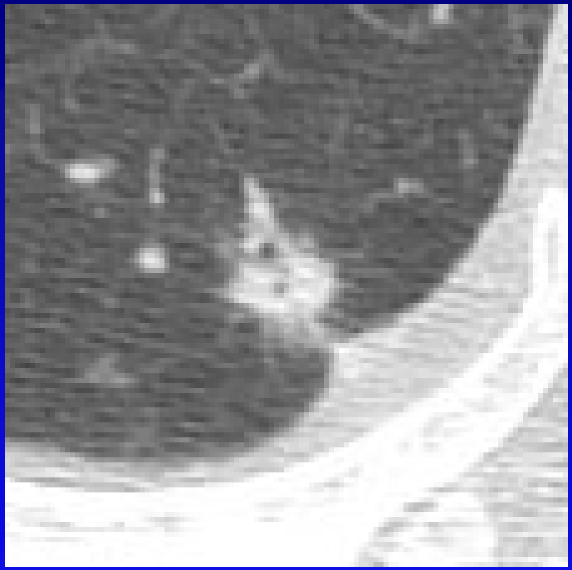
Benign nodule

Initial rating (0-1.0): 0.46
Computer output: 0.01
2nd rating: 0.27

F. Li et al. AJR 183: 1209-1215, 2004

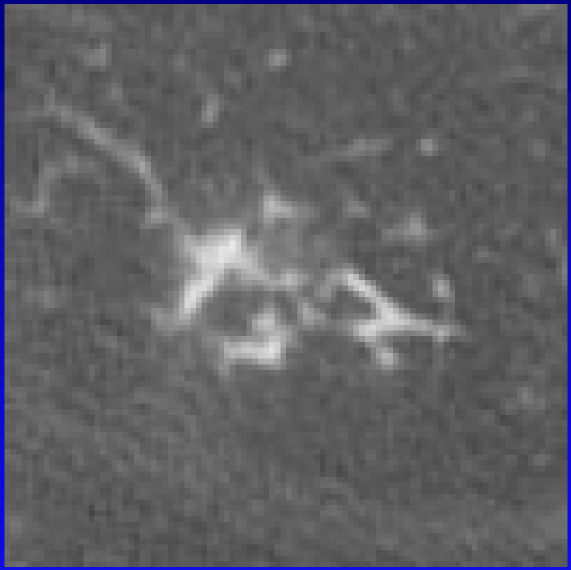
“Obvious” Cases to Radiologists :

Radiologists Maintained Their Correct Decision Despite Incorrect Computer Result



Malignant nodule

Initial rating (0-1.0): 0.67
Computer output: 0.37
2nd rating: 0.61

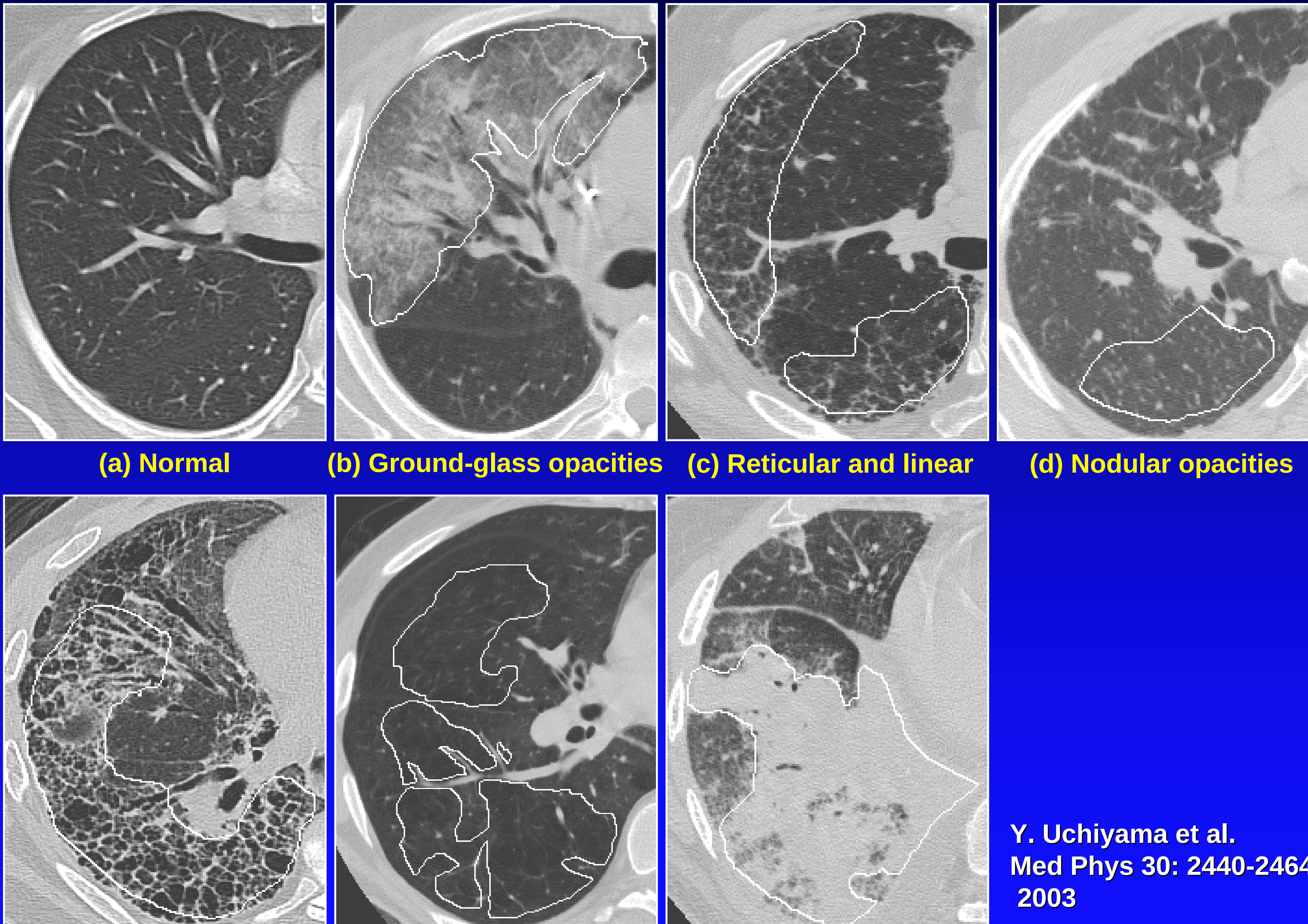


Benign nodule

Initial rating (0-1.0): 0.21
Computer output: 0.60
2nd rating: 0.31

F. Li et al. AJR 183: 1209-1215, 2004

CAD for Diffuse Lung Diseases in HRCT

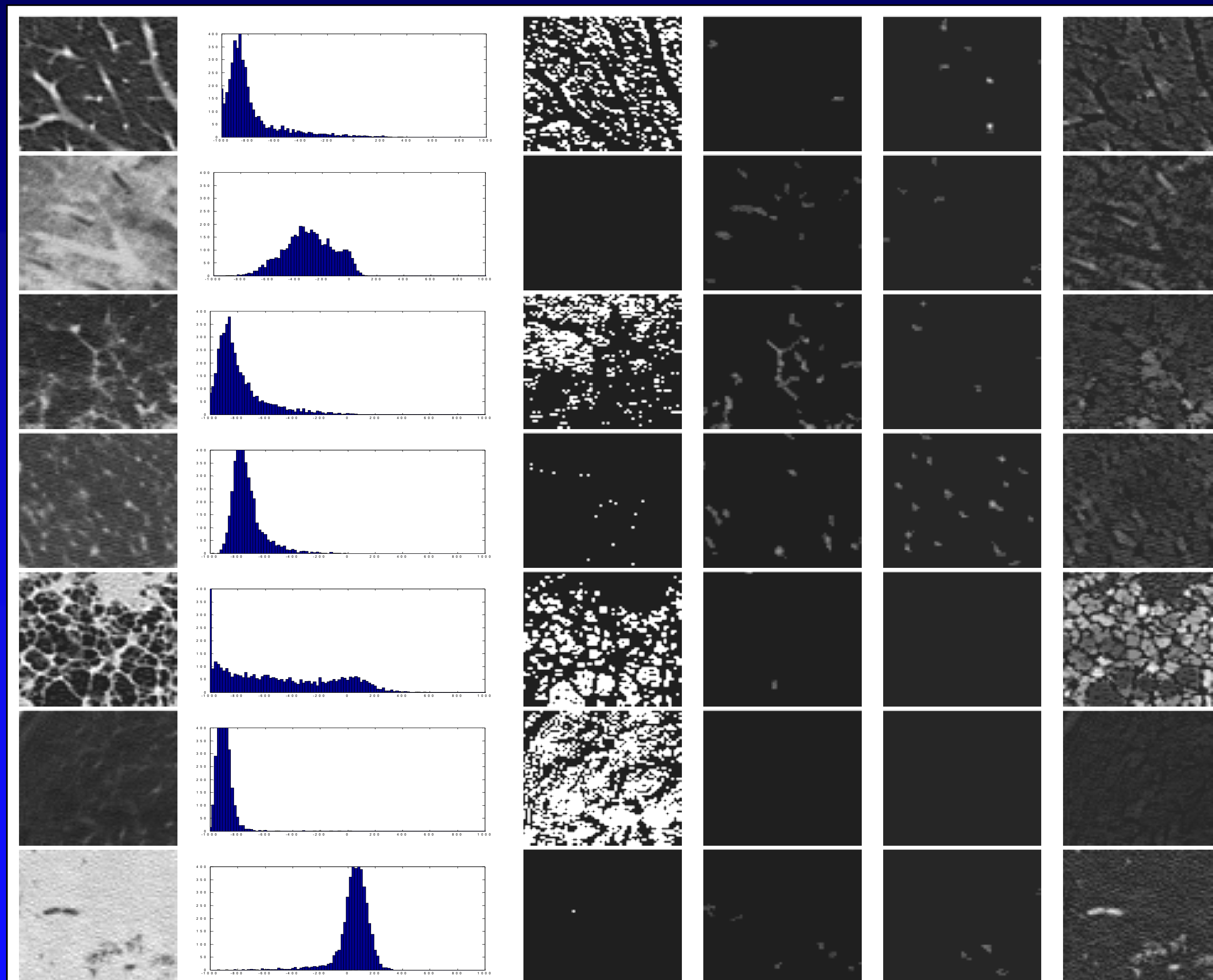


(a) Normal (b) Ground-glass opacities (c) Reticular and linear (d) Nodular opacities

(e) Honeycombing (f) Emphysematous change (g) Consolidation

Y. Uchiyama et al.
Med Phys 30: 2440-2464,
2003

Original ROI | Histogram of CT value | Air density component | Line component | Nodular component | Multilocular component



Normal

Ground-glass opacities

Reticular and linear

Nodular opacities

Honeycombing

Emphysematous change

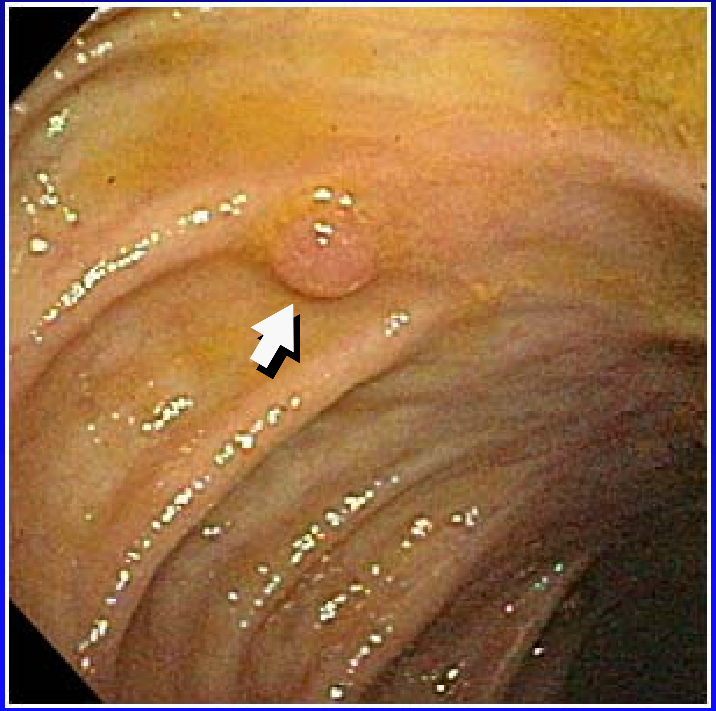
Consolidation

Computerized Classification Results of ROIs obtained from “Gold Standard”

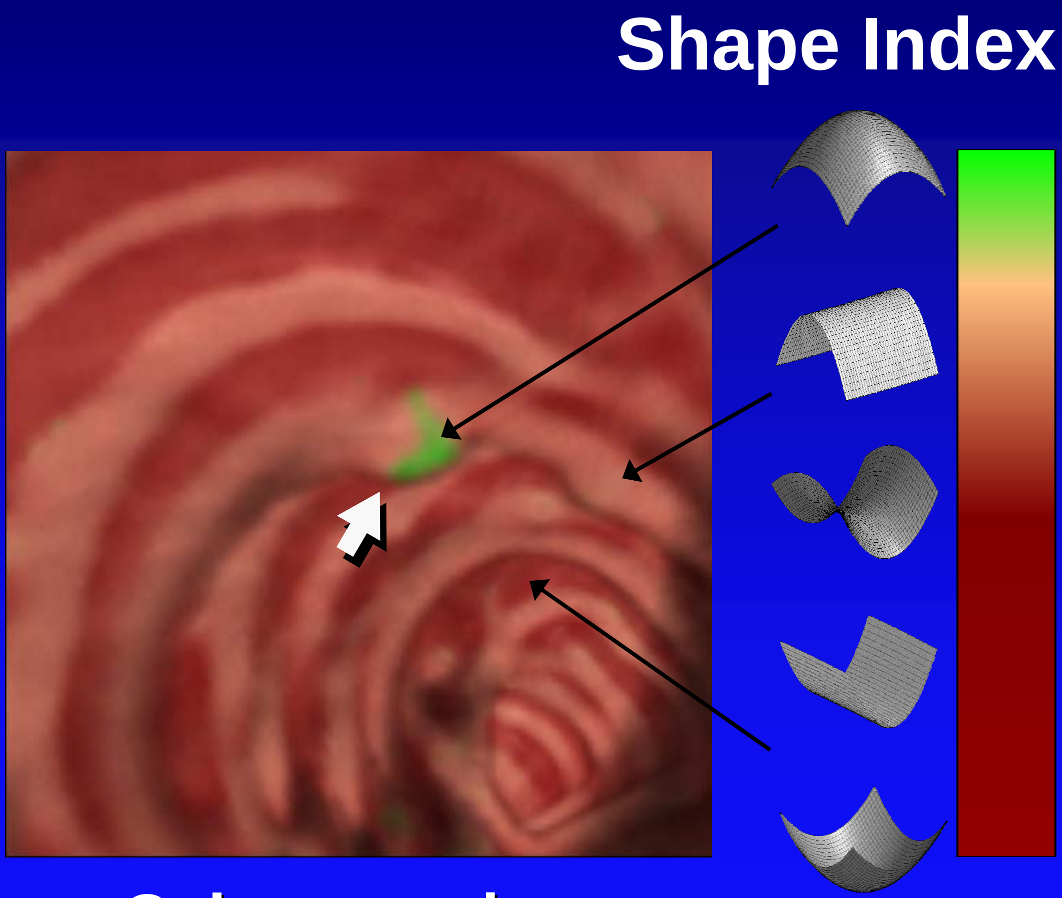
Normals	88.1% (940 /1067)
Ground-glass opacities	99.2% (122 /123)
Reticular and linear opacities	100.0% (15 /15)
Nodular opacities	88.0% (132 /150)
Honeycombing	100.0% (98 /98)
Emphysematous change	95.8% (369 /385)
Consolidation	100.0% (43 /43)

Y. Uchiyama et al. Med Phys 30: 2440-2464, 2003

Detection of Polyp Candidates in CT Colonography



Colonoscopy



Colonography

H. Yoshida et al. Radiology 222: 327-336, 2002

What are the important issues related to CAD ?

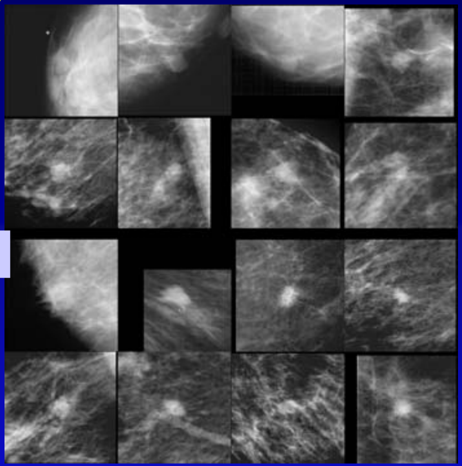
1. Clear evidence of clinical usefulness
2. Low performance levels of computerized schemes
3. Lack of large databases
4. Detection vs classification

A Major Challenge?

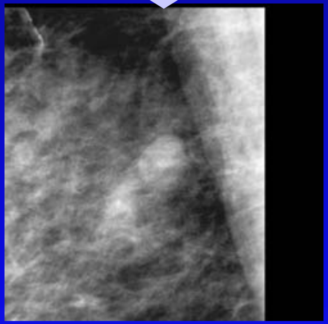
The vast majority of images stored in PACS are currently **“sleeping”,** since these images have not been used for clinical purposes.

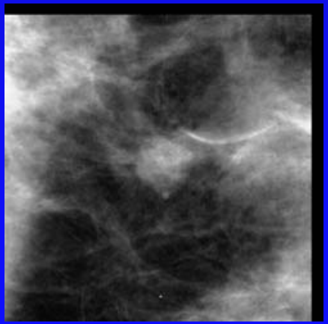
Can these **sleeping images** be utilized for daily clinical purposes?

Potential Usefulness of Similar Images in Screening Mammography

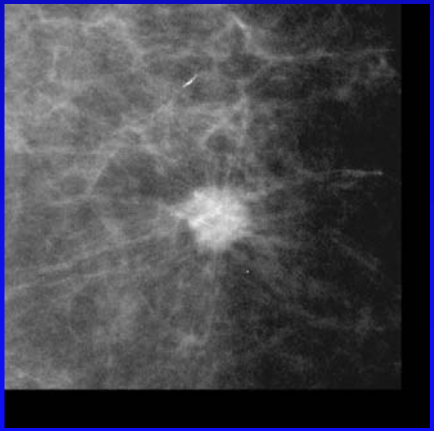


Database or PACS

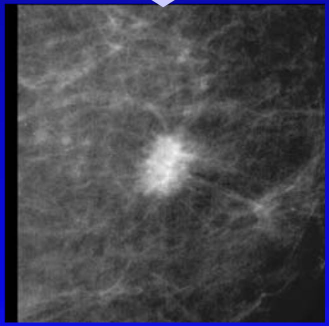


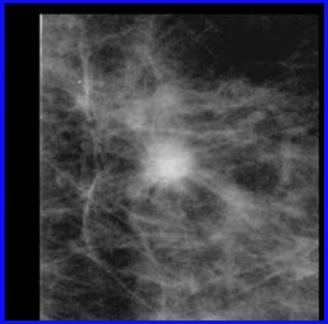


Benign



Unkown Cancer case





Cancer

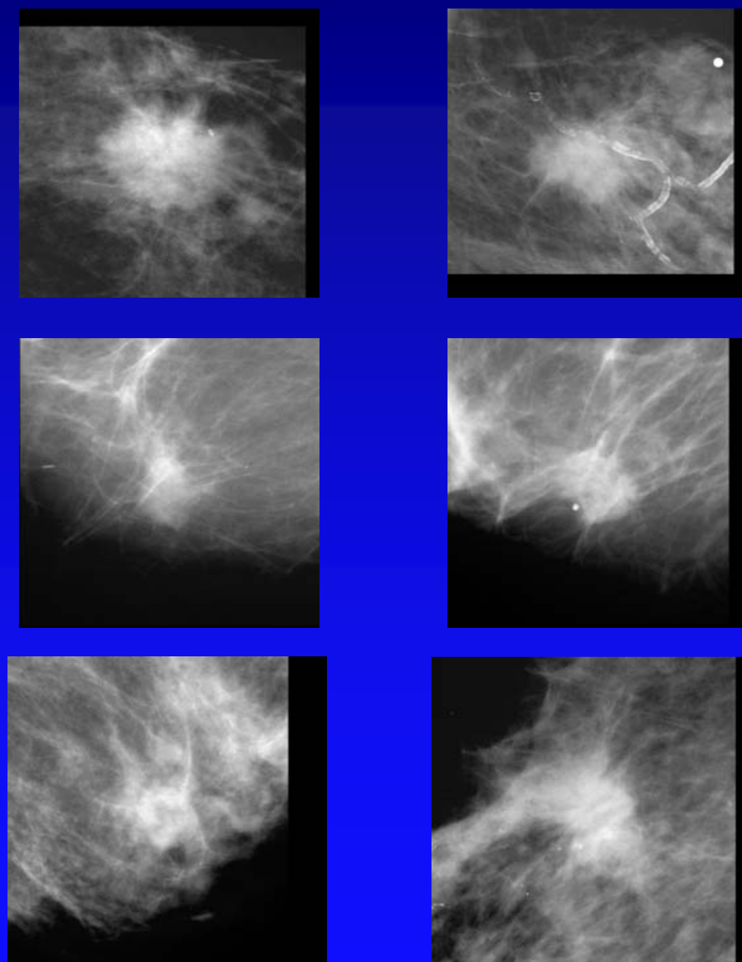
How can similar images be retrieved from database?

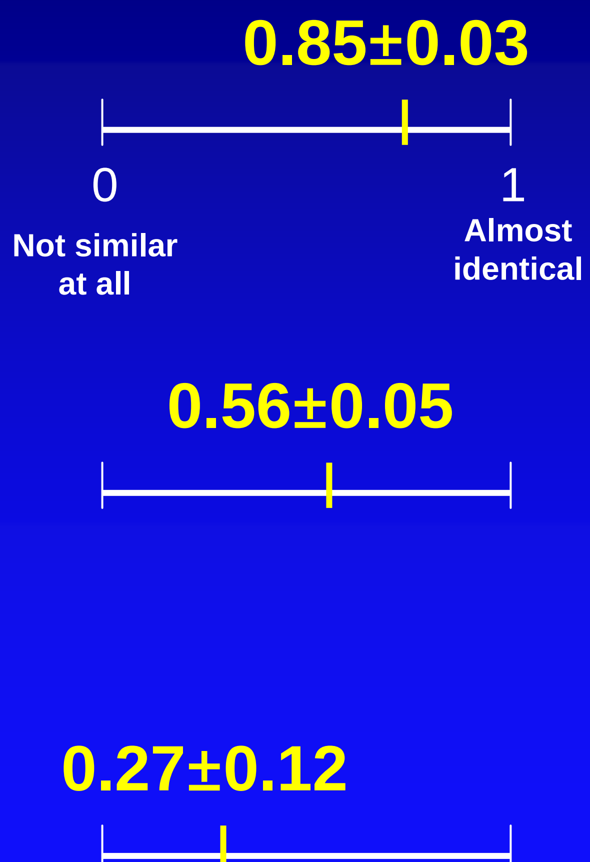
How can the similarity be measured and quantified?

Subjective Similarity of Masses on Mammograms

Subjective Similarity Ratings by Radiologists: Average Values and Standard Deviations

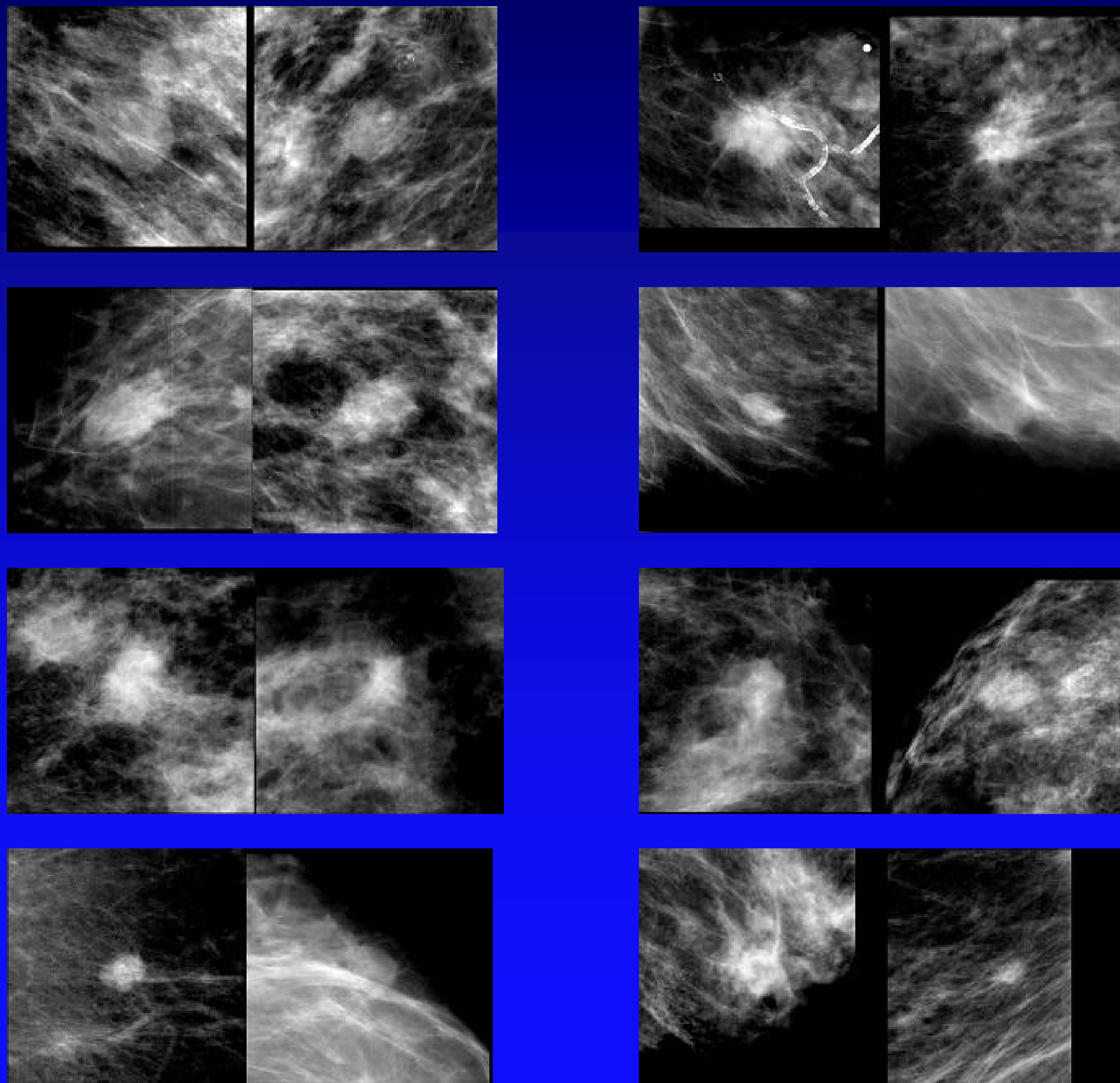
Pairs of Mass Lesions





Muramatsu et al. Med Phys 32: 2295-2304, 2005

Subjective Similarity Ratings for Eight Pairs of Breast Masses on Mammograms



0.81

0.73

0.61

0.53

0.43

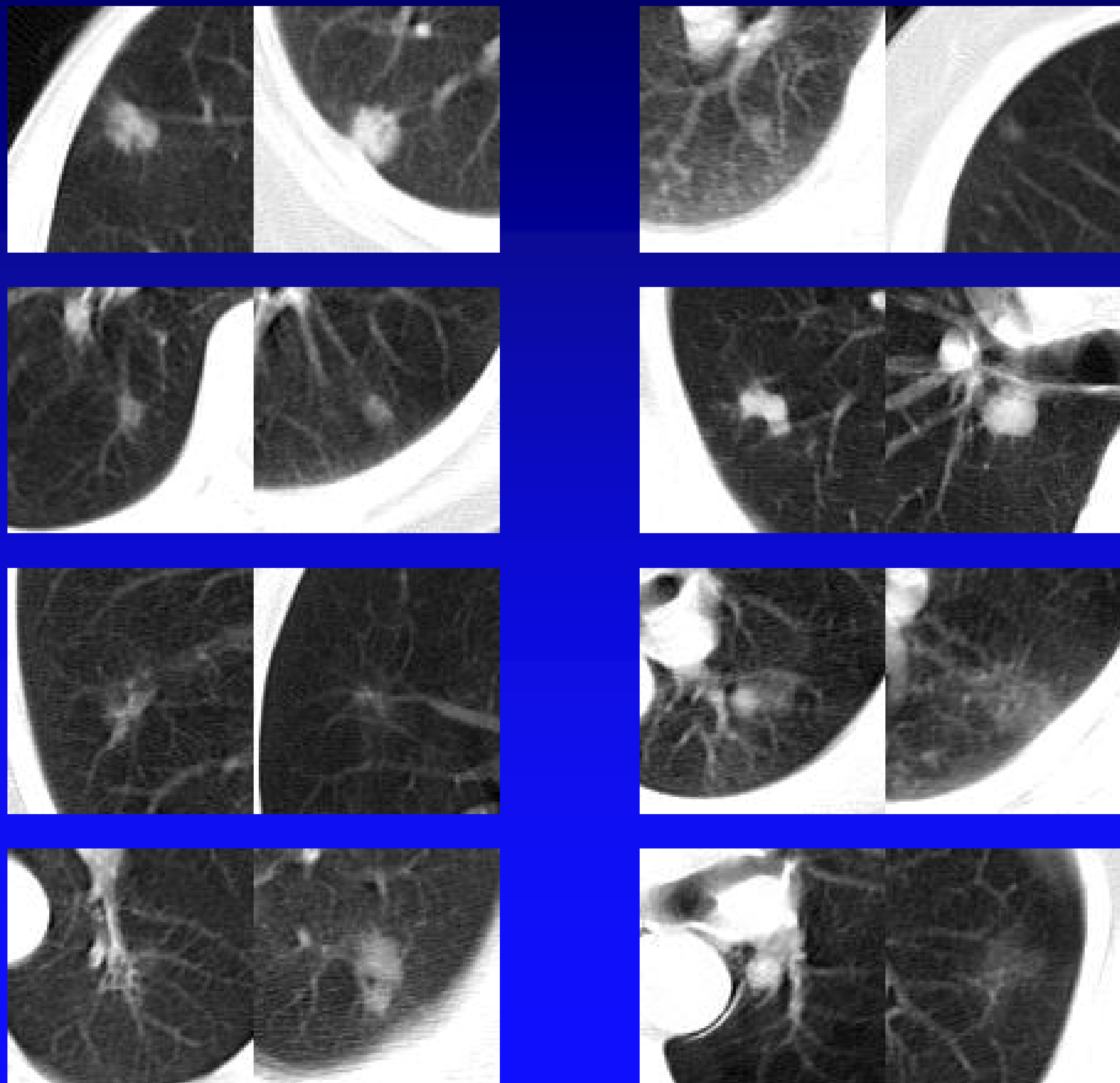
0.33

0.27

0.15

Subjective Similarity of Lung Nodules in CT Images

Subjective Similarity Ratings for Eight Pairs of Lung Nodules on CT images



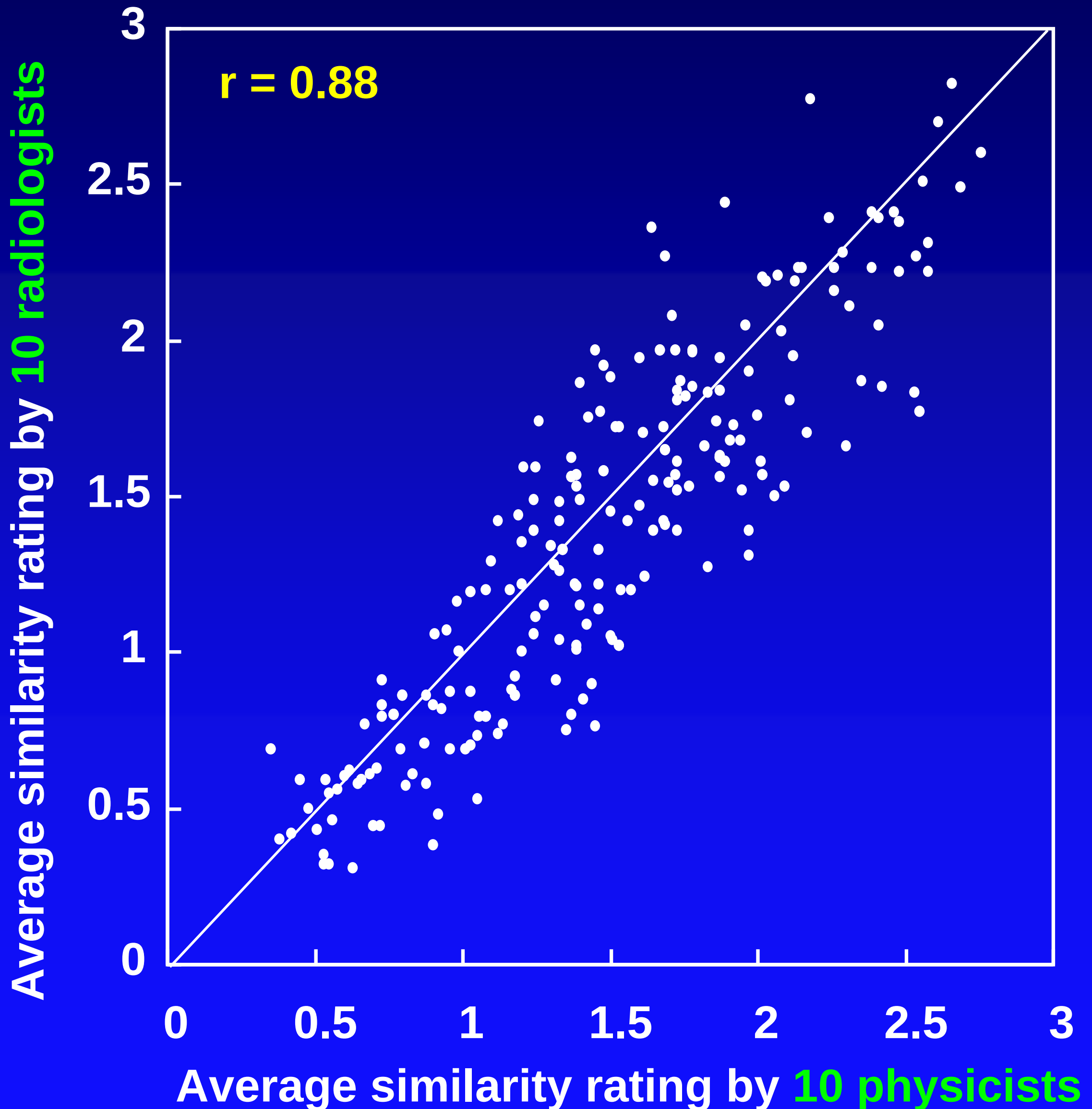
0.84 | 0.70

0.59 | 0.50

0.39 | 0.31

0.19 | 0.11

Relationship on Subjective Similarity Ratings between Radiologists and Physicists

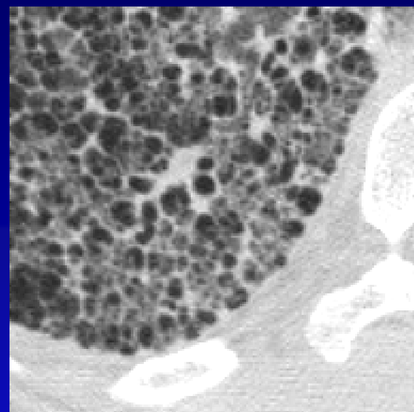


Q. Li et al. Med Phys 30: 2594-2593, 2003

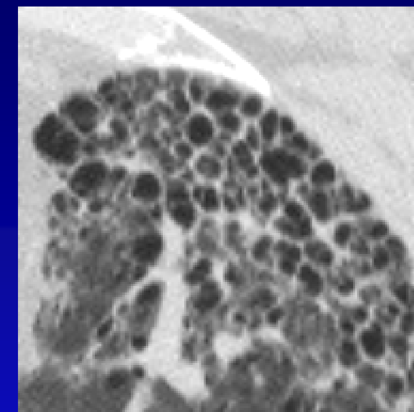
Subjective Similarity for Pairs of Images with Various Patterns of Diffuse Lung Disease on Thin-Section CT

Randomly Selected Same Pattern Pair

Honeycombing

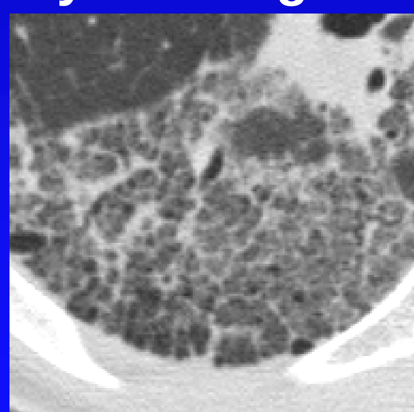


Honeycombing

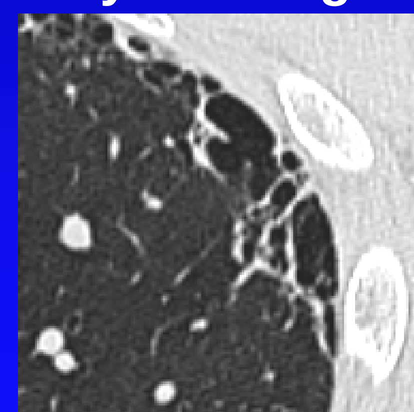


Similarity: 0.88 ± 0.03

Honeycombing + GGO



Honeycombing + Nodular



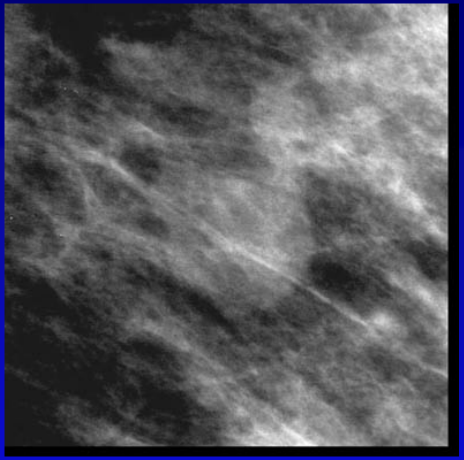
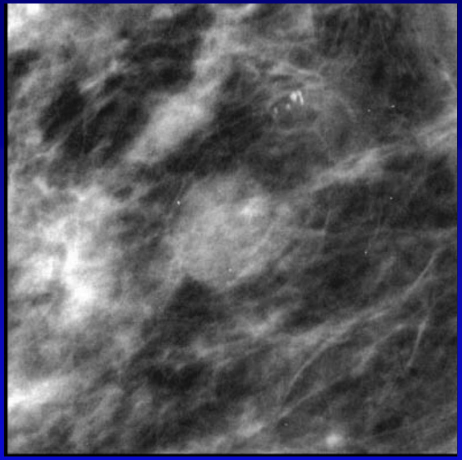
Similarity: 0.13 ± 0.05

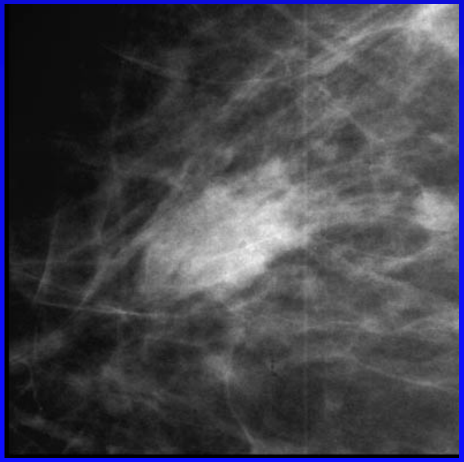
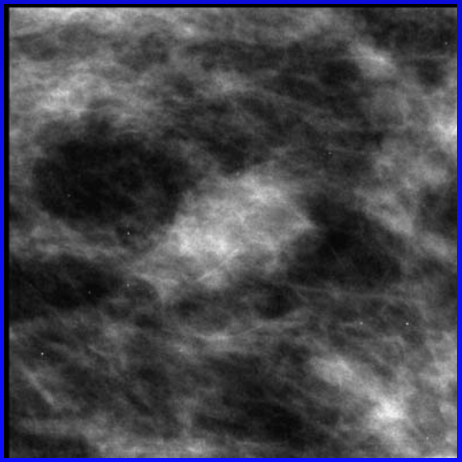
F. Li et al. Acad Rad 16: 477- 485, 2009

Quantitation of Relative Similarity: Comparison of Mammographic Similar Lesions by use of 2AFC Method

2AFC: Two alternative forced choice

Comparison of Similarities: Two Pairs of Masses

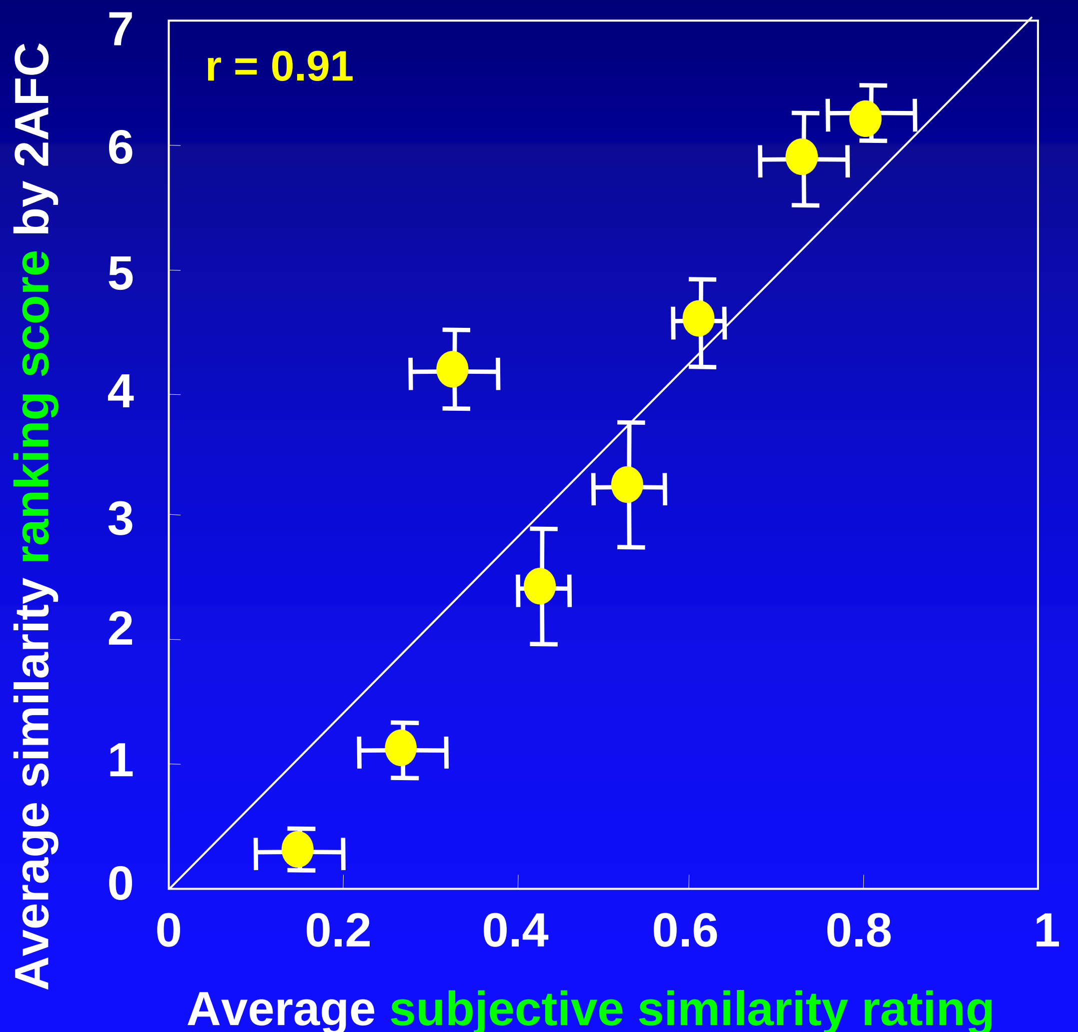



Upper pair (16 / 20) : 0.8

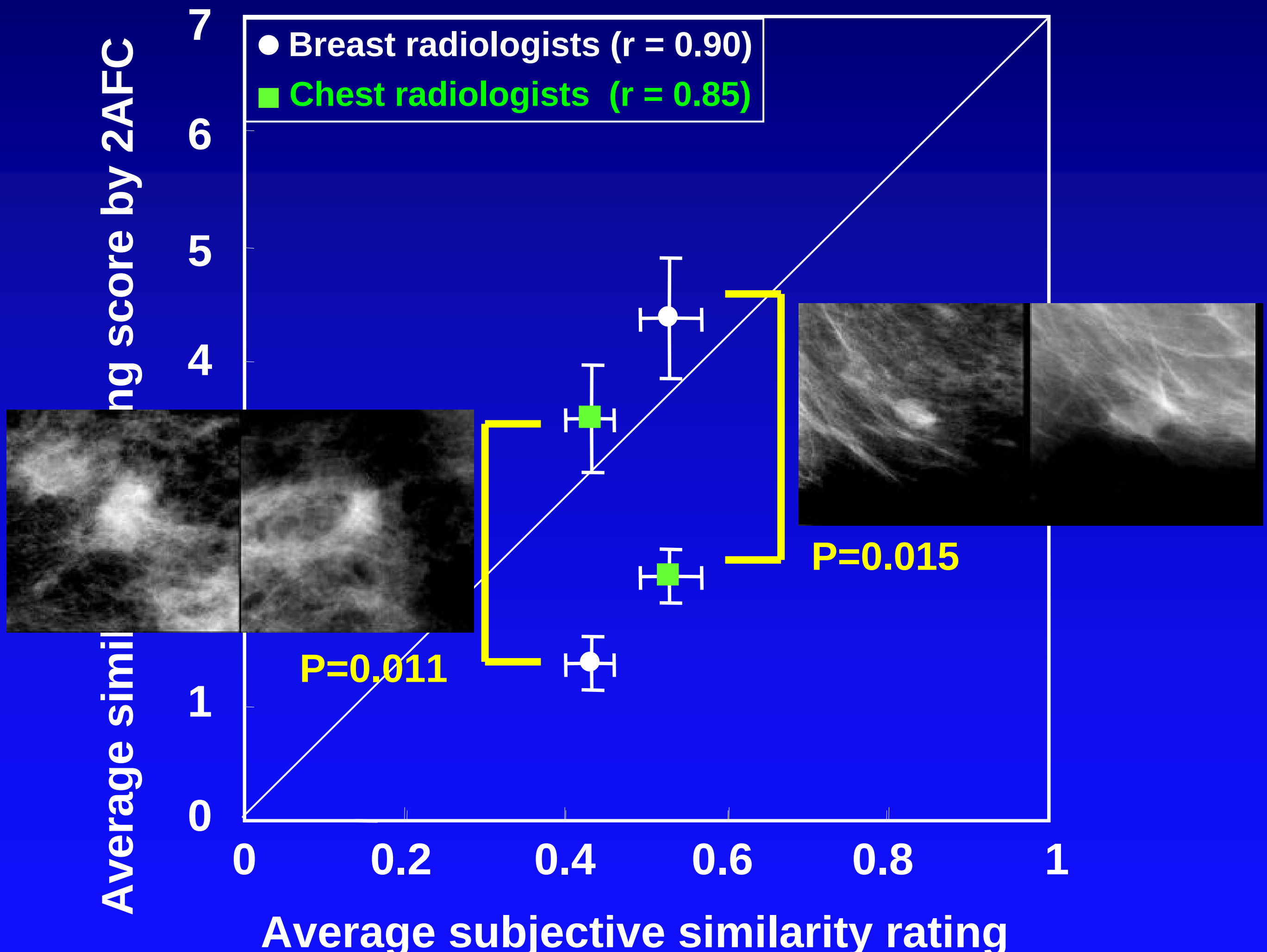
Ranking score:
Total no. of selections from all comparisons

Which is more similar?
Upper or lower pair?

Subjective Similarity Ratings and Similarity Ranking Scores for Eight Mass Pairs



Subjective Similarity Ratings and Similarity Ranking Scores for Eight Mass Pairs

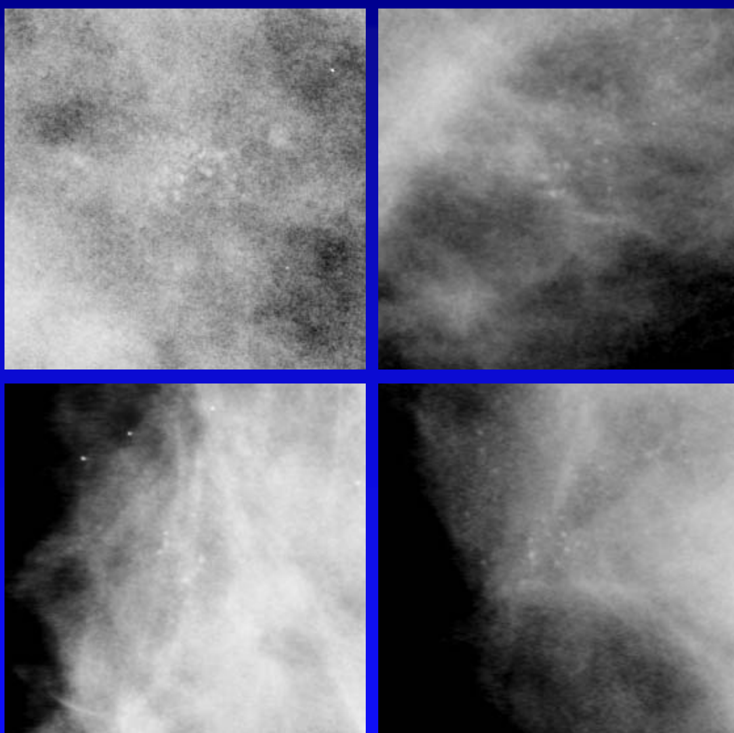


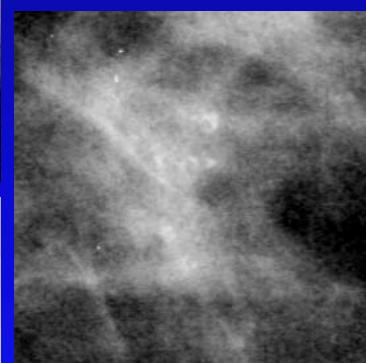
Kumazawa et al. Acad Radol 15: 887-894, 2008

Usefulness of Similar Images for Distinction between Benign and Malignant Lesions on Mammograms

Unknown Malignant Microcalcification Case with Beneficial Change by use of Similar Images

Similar benign lesions

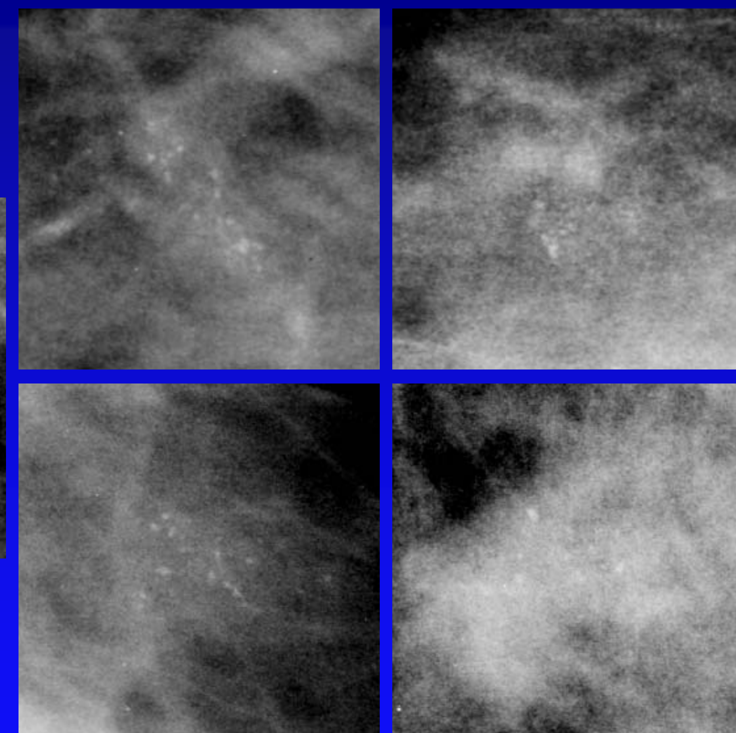




Unknown case

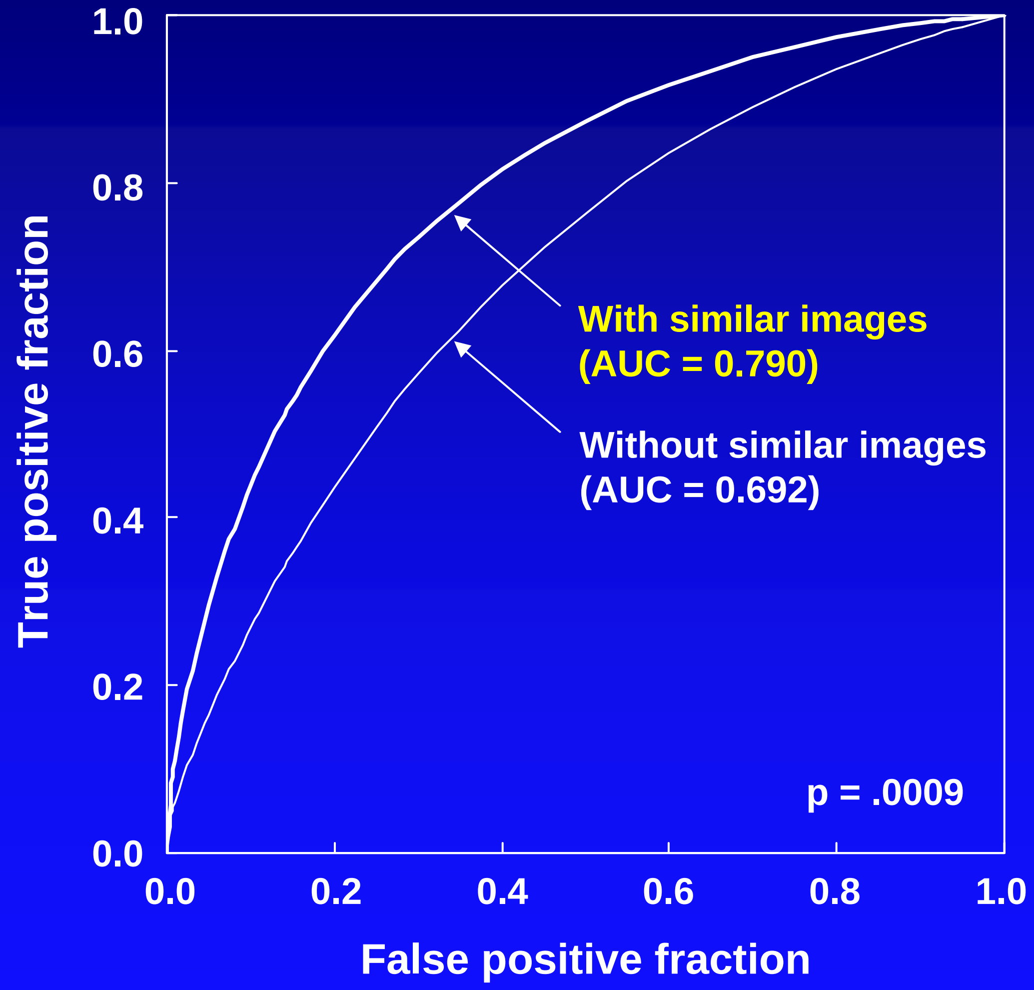
Malignant

Similar malignant lesions



Average confidence level : 0.491 Increased to 0.605

Improved Performance due to Similar Images for Distinction between Benign and Malignant Microcalcifications



R. Nakayama et al. Radiology 253: 625-631, 2009

Computer-Aided Diagnosis: Where will it be in Five Years?

1. Improved CAD performances
2. Integration of CAD into PACS and workstations
3. CAD as diagnostic tool plus educational tool with large image databases
4. Standard diagnostic care with reimbursement

Conclusion:

It is likely that CAD will have a significant impact on diagnostic radiology and medical physics in the future.