MAYO CLINIC

Center for Tuberculosis

Artificial Intelligence and TB X-Ray Interpretation

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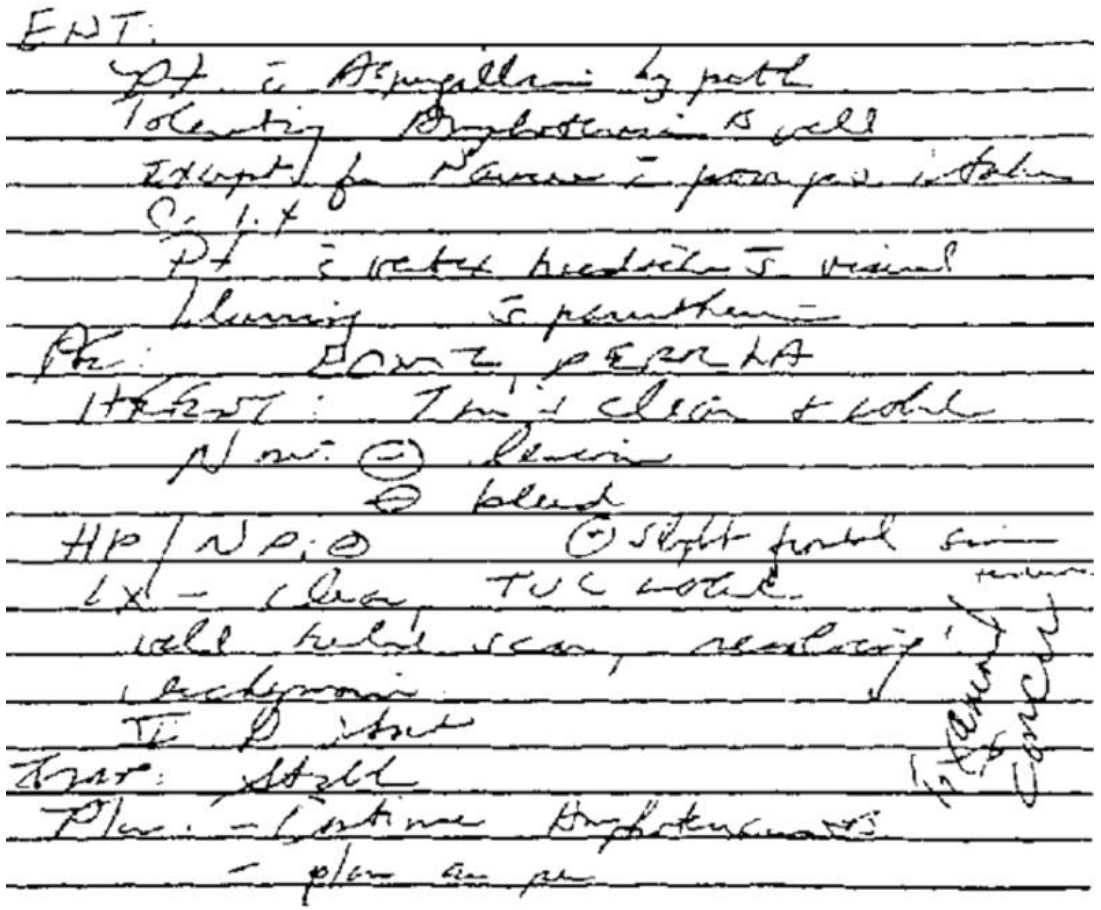
Artificial Intelligence

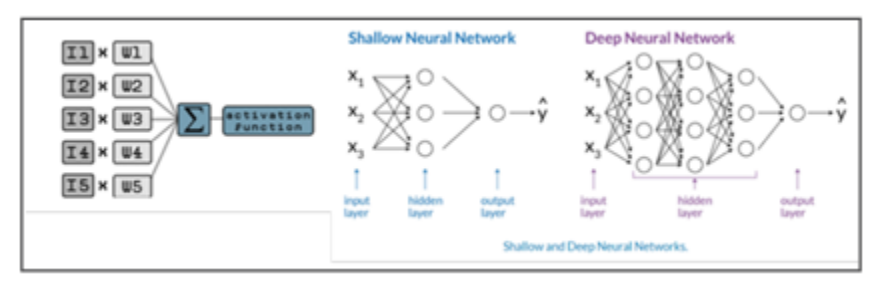
Tuna



“The patient has a normal physical exam, and normal labs”

AI x-ray interpretation

COMPUTER AIDED DETECTION (CAD) FOR TUBERCULOSIS



AI x-ray interpretation

COMPUTER AIDED DETECTION (CAD) FOR TUBERCULOSIS

How are we going to “instruct” our algorithm to recognize TB?

= TB

Not = TB

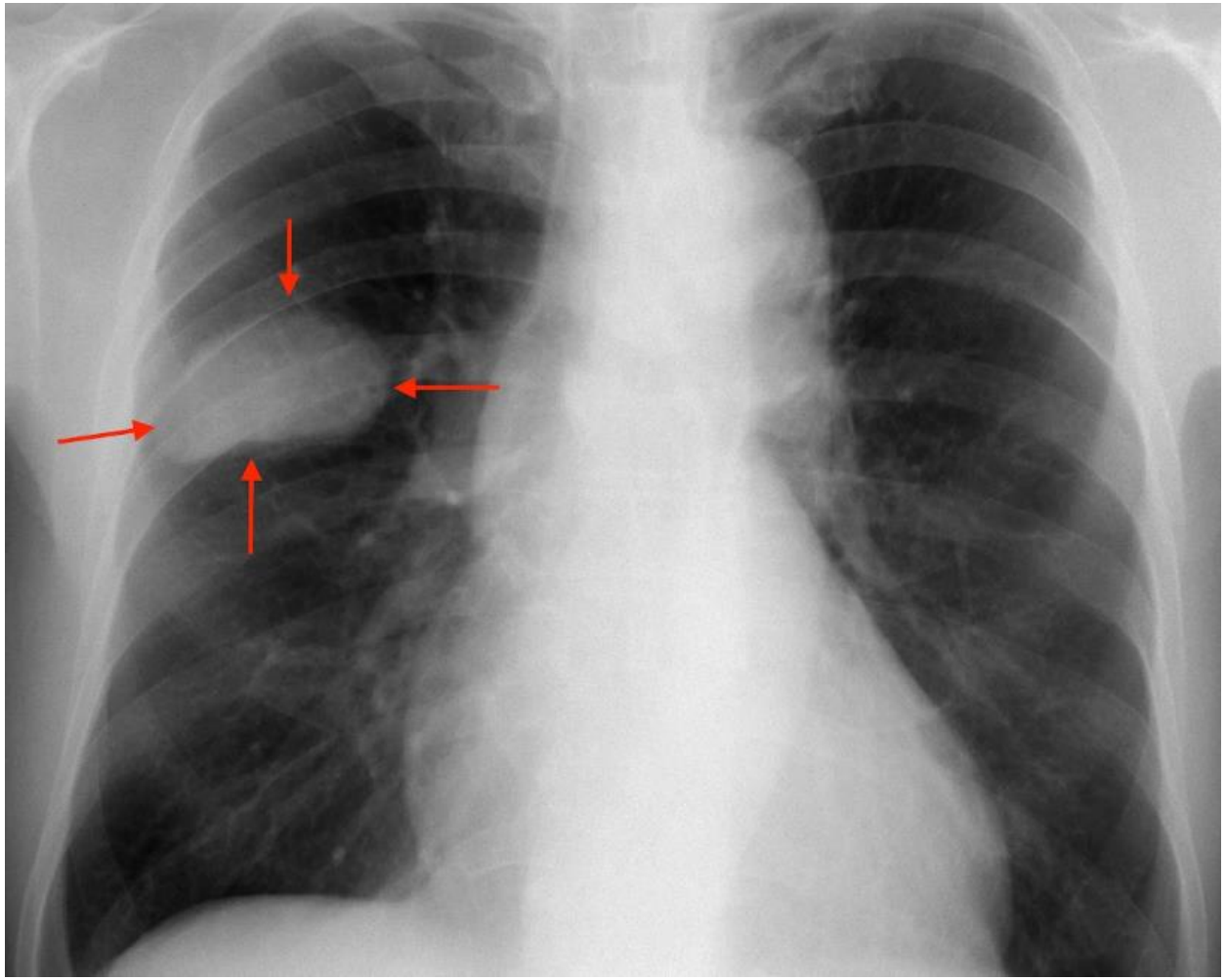
What do we consider to be TB for our training set?

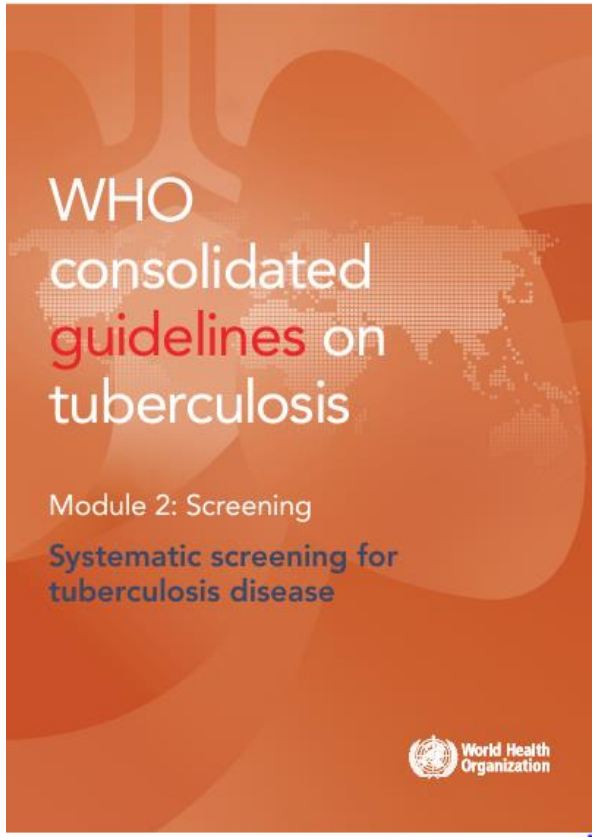
- Microbiologic confirmation
- Clinical case
- Radiologist confirmed

What population characteristics?

- Age
- HIV-status
- Region/population
- Disease severity
- BMI
- Sex
- Pregnancy
- Co-morbidities (e.g. diabetes)
- Prior TB
- Smoking
- Symptoms

What do we want the tool to do about non-TB abnormalities?





Type of case and type of reader	Accuracy estimate range	
	Sensitivity	Specificity
WHO target product profile	> 0.90	> 0.70
Screening use case		
CAD software	0.90–0.92	0.23–0.66
CXR with human reader	0.82–0.93	0.14–0.63
Triage use case		
CAD software	0.90–0.91	0.25–0.79
CXR with human reader	0.89–0.96	0.36–0.63

10. Among individuals aged 15 years and older in populations in which TB screening is recommended, computer-aided detection software programmes may be used in place of human readers for interpreting digital chest X-rays for screening and triage for TB disease

(new recommendation: conditional recommendation, low certainty of evidence).

Current product landscape

Computer-aided detection of tuberculosis from chest radiographs in a tuberculosis prevalence survey in South Africa: external validation and modelled impacts of commercially available artificial intelligence software

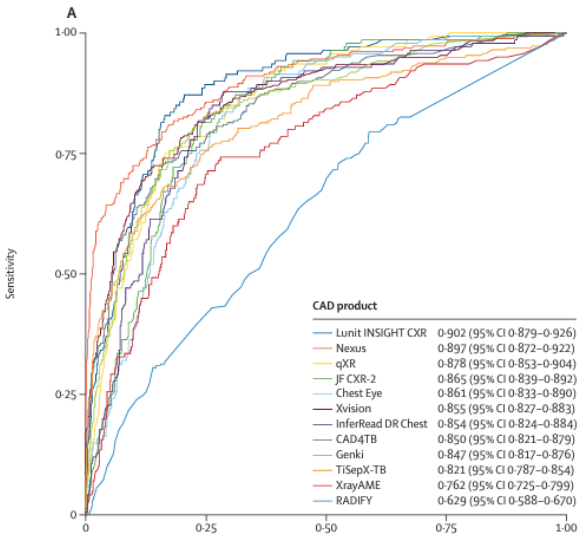
Zhi Zhen Qin, Martie Van der Walt*, Sizulu Moyo, Farzana Ismail, Phaleng Maribe, Claudia M Denkinger, Sarah Zaidi, Rachael Barrett, Lindiwe Mvusi, Nkateko Mkhondo, Khangelani Zuma, Samuel Manda, Lisa Koeppel, Thuli Mthiyane†, Jacob Creswell†*

***Lancet Digit Health* 2024; 6: e605–13**

	Threshold	Sensitivity	Specificity
Threshold to match 90% sensitivity			
Lunit	0·07	89·9% (85·6–93·3)	67·7% (63·5–71·7)
Nexus	0·48	89·9% (85·6–93·3)	67·1% (62·9–71·2)
JF CXR-2	0·23	89·5% (85·1–93·0)	62·7% (58·3–66·9)
qXR	0·18	90·3% (86·0–93·6)	62·3% (57·9–66·5)
ChestEye	0·08	89·1% (84·7–92·7)	61·3% (57·0–65·5)
Xvision	0·11	89·9% (85·6–93·3)	58·6% (54·2–62·9)
CAD4TB	3	89·9% (85·6–93·3)	55·7% (51·3–60·0)
InferRead	0·26	90·3% (86·0–93·6)	54·9% (50·5–59·3)
Genki	0·02	89·5% (85·1–93·0)	54·5% (50·1–58·9)
TiSepX-TB	0·18	89·9% (85·6–93·3)	48·0% (43·6–52·4)
XrayAME	0·02	88·4% (83·8–92·0)*	36·9% (32·8–41·3)
RADIFY	0·02	82·6% (77·4–87·0)*	32·5% (28·5–36·7)
Threshold to match 70% specificity			
Lunit	0·09	89·5% (85·1–93·0)	70·2% (66·1–74·1)
Nexus	0·54	88·8% (84·3–92·3)	69·8% (65·7–73·8)
qXR	0·32	86·8% (82·1–90·7)	70·2% (66·1–74·1)
JF CXR-2	0·4	86·4% (81·6–90·4)	70·0% (65·9–73·9)
ChestEye	0·11	86·0% (81·2–90·0)	69·6% (65·5–73·6)
InferRead	0·37	85·7% (80·8–89·7)	70·4% (66·3–74·3)
Xvision	0·14	85·7% (80·8–89·7)	69·6% (65·5–73·6)
Genki	0·09	84·5% (79·5–88·7)	70·6% (66·5–74·5)
CAD4TB	12	81·0% (75·7–85·6)	70·6% (66·5–74·5)
TiSepX-TB	0·29	77·5% (71·9–82·5)	70·8% (66·7–74·7)
XrayAME	0·13	68·6% (62·6–74·2)	70·6% (66·5–74·5)
RADIFY	0·57	43·4% (37·3–49·7)	71·0% (66·9–74·9)†

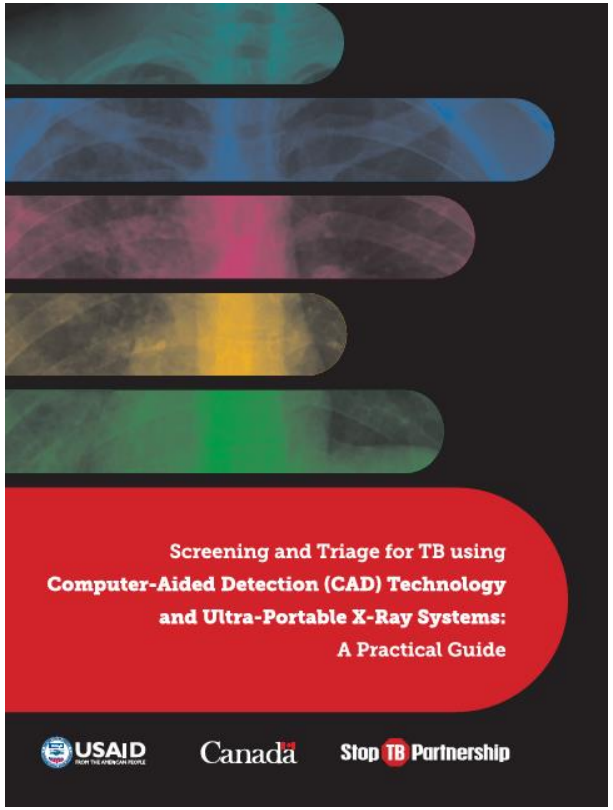
*The closest sensitivity to 90%. †The closest specificity to 70%.

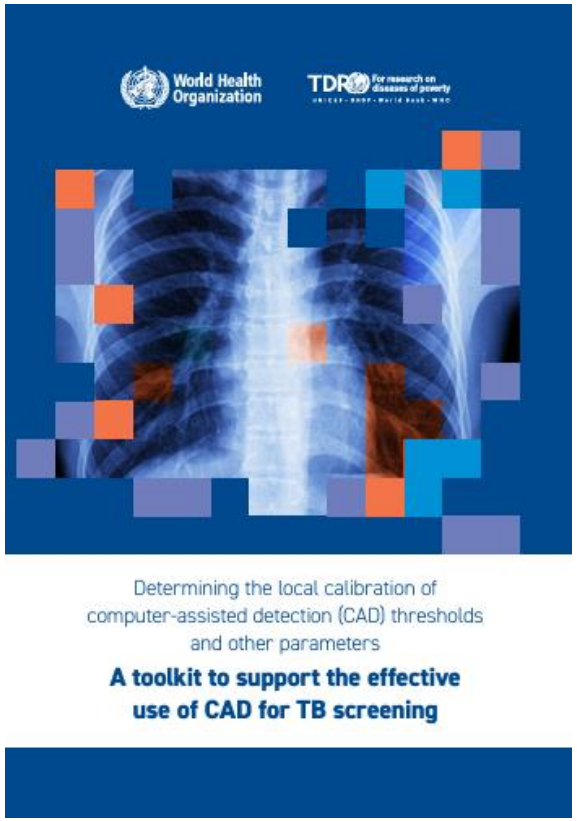
Table 2: **Computer-aided detection performance compared with 90% sensitivity and 70% specificity target values**



Implementation Considerations

- Objectives
- Local validation
- Product
- Threshold
- Resources
- Integration with current work-flow





What use case?

What objective?

SCREENING

Population → X-Ray → Evaluation

TRIAGE

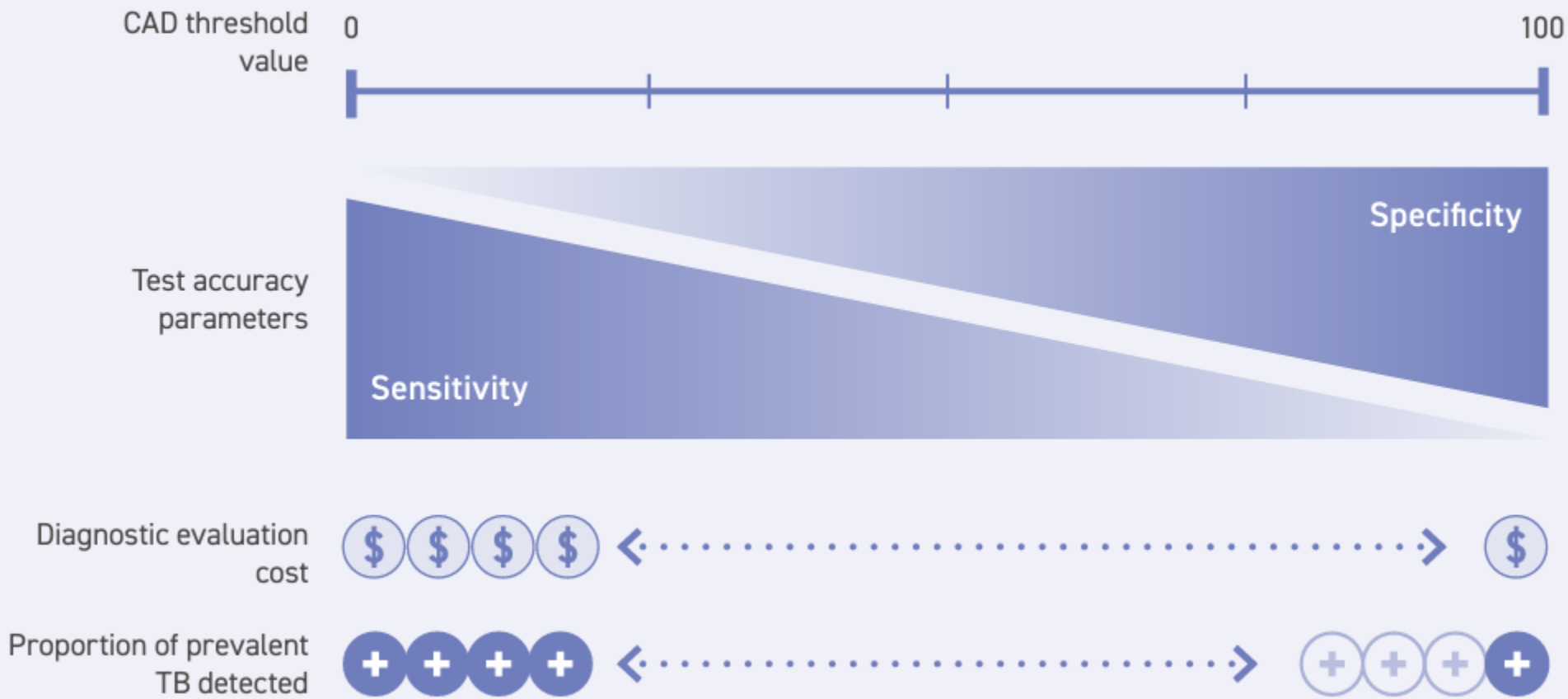
Clinical suspicion → X-Ray → Evaluation

Implementation Considerations

- Product

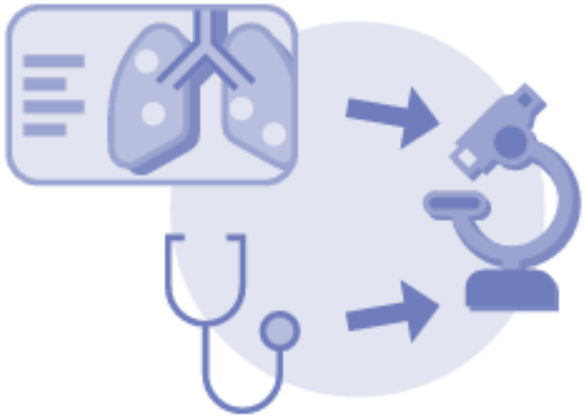
ai4hlth.org is a regularly updated online marketplace of CAD products for TB.

Figure 1: Sensitivity vs. specificity across CAD threshold spectrum



Integration and operationalization

All x-rays read by CAD. Abnormal x-rays (and subset of normal) read by radiologist prior to work-up



All x-rays read by CAD and radiologist. Any abnormal x-ray from either gets work-up

Thank you