Artificial Intelligence and Computer Aided Diagnosis in Radiology

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WHO CRES Committee Member

University of the Witwatersrand

A.I. Artificial Intelligence

I, Robot

Bicentennial Man

Blade Runner

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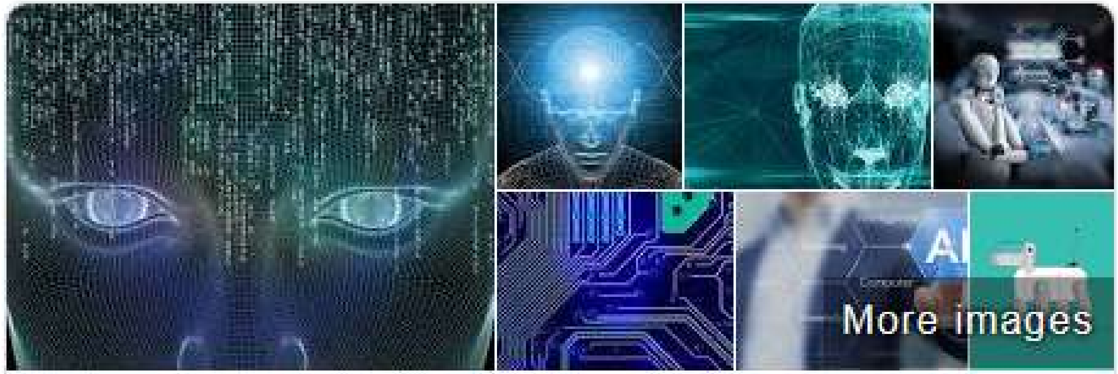

Artificial intelligence

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INNOVATION

AI Will Change Radiology, but It Won’t Replace Radiologists

by Thomas H. Davenport and Keith J. Dreyer, DO

MARCH 27, 2018

University of the Witwatersrand

Pediatric Radiology (2019) 49:509–516
https://doi.org/10.1007/s00247-018-4277-7

MINISYMPOSIUM: QUALITY AND SAFETY

Machine learning concepts, concerns and opportunities for a pediatric radiologist

Michael M. Moore[1] · Einat Slonimsky[1] · Aaron D. Long[1] · Raymond W. Sze[2] · Ramesh S. Iyer[3]

Received: 2 July 2018 / Revised: 27 August 2018 / Accepted: 2 October 2018 / Published online: 14 March 2019

Abstract

Radiology

REVIEWS AND COMMENTARY ■ EDITORIAL

Deep Learning Lends a Hand to Pediatric Radiology[1]

Ronald M. Summers, MD, PhD

Machine learning in radiology is a hot topic. A part of computer science, machine learning is a field in which systems can be designed and trained to learn concepts from data to make predictions. Machine learn-

original clinical report. The authors determined the differences in the bone ages calculated by the computer model and those of the human observers by using a pairwise analysis. They calculated these differences two ways. The

Definitions

- **Artificial intelligence**: The academic field that studies how to create computers and computer software that can perform tasks that ordinarily require human intelligence
- **Machine learning:** A subfield of artificial intelligence in which algorithms are trained to perform tasks by learning patterns from data rather than by explicit programming

Definitions

- **Deep learning**: A type of machine learning in which the algorithm learns on its own the best features to classify the provided data. Convolutional neural networks is a commonly utilized specific type of deep learning
- **Classification:** Predicting the target class from an image or region of interest within the image

The Role of Artificial Intelligence in Radiology in Africa

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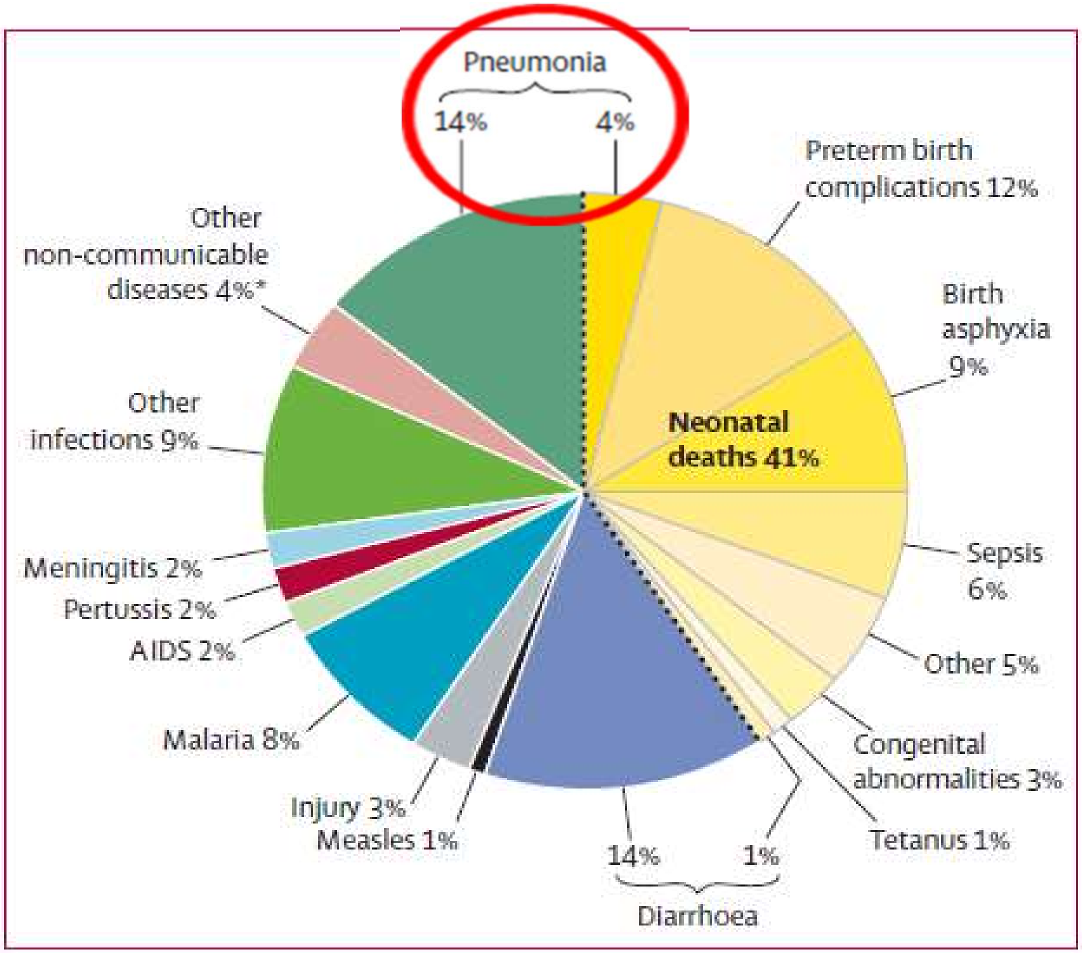
Computer Aided Diagnosis for WHO Primary Endpoint Pneumonia on Chest X-Ray in Children under 5 years

Introduction



Black RE, Cousens S, Johnson HL, et al. Global, regional, and national causes of child mortality in 2008: a systematic analysis. Lancet. 2010 Jun 5;375(9730):1969-87.

Introduction

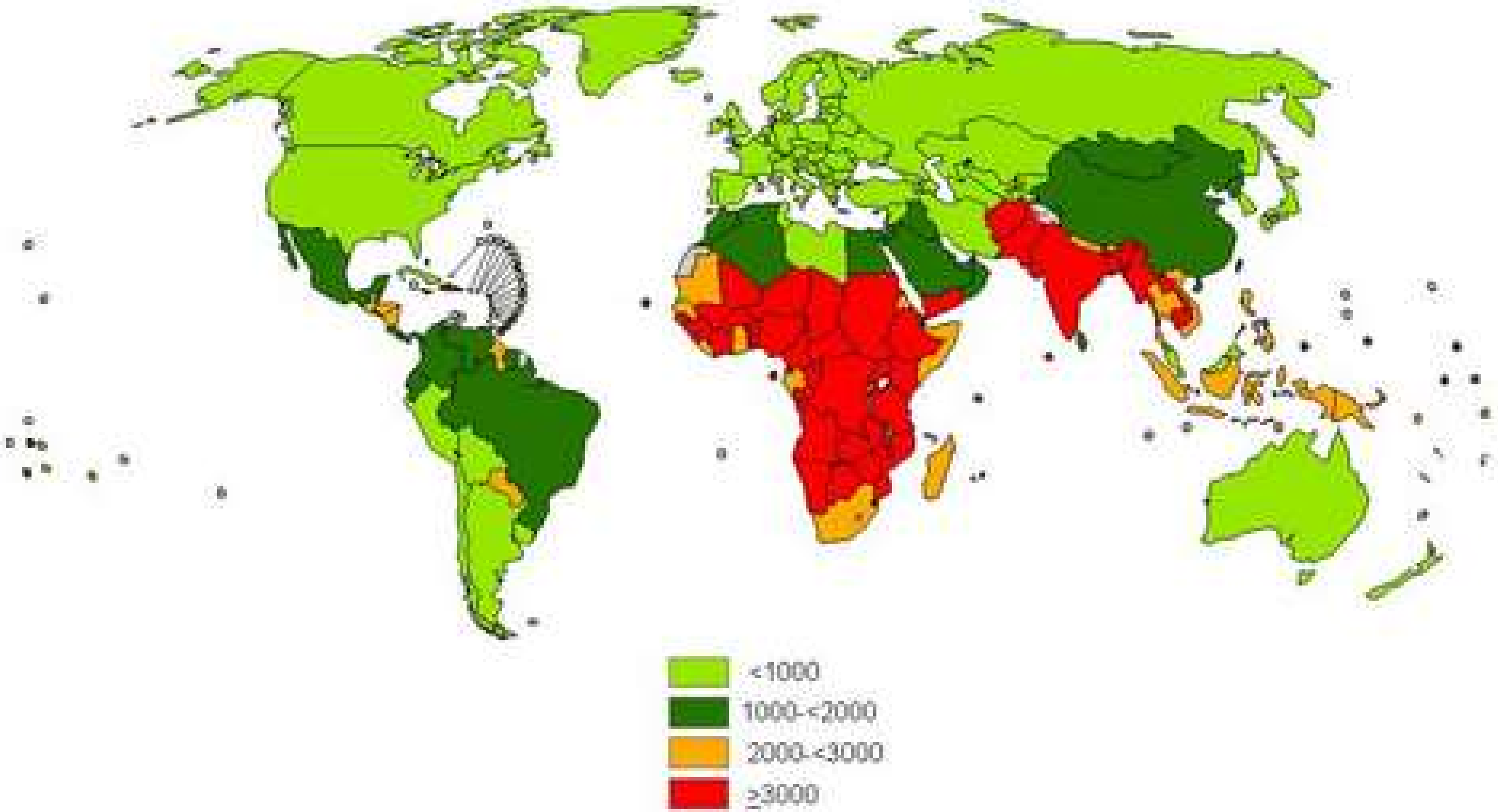
- Pneumonia is the leading infectious cause of morbidity and mortality in children less than 5 years globally
- Streptococcus pneumoniae (pneumococcus) and Haemophilus influenzae type b (Hib) are the most important causes of vaccine-preventable deaths in children <5 years

Black RE, Cousens S, Johnson HL, et al. Global, regional, and national causes of child mortality in 2008: a systematic analysis. Lancet. 2010 Jun 5;375(9730):1969-87.

O'Brien KL, Wolfson LJ, Watt JP, et al. Burden of disease caused by Streptococcus pneumoniae in children younger than 5 years: global estimates. Lancet. 2009 Sep 12;374(9693):893-902.

Watt JP, Wolfson LJ, O'Brien KL, et al. Burden of disease caused by Haemophilus influenzae type b in children younger than 5 years: global estimates. Lancet. 2009 Sep 12;374(9693):903-11.

SP incidence rate
(per 100000 children under age 5)



United Nations Child Mortality SP estimates-2013

The Chest X-Ray

- The chest X-ray remains the most readily available and commonest imaging modality for the assessment of childhood pneumonia
- The number of paediatric radiologists in low income countries is limited

- Pitcher RD, Lombard C, Cotton MF, et al. Clinical and immunological correlates of chest X-ray abnormalities in HIV-infected South African children with limited access to anti-retroviral therapy. Pediatr Pulmonol. 2013. Jun;49(6):581-8.
- Cherian T, Mulholland EK, Carlin JB, et al. Standardized interpretation of paediatric chest radiographs for the diagnosis of pneumonia in epidemiological studies. Bull World Health Organ. 2005 May;83(5):353-9.

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WFPI | The World Federation of Pediatric Imaging

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Global map of availability of Pediatric Radiologists

Population <19 years per Pediatric Radiologist / country

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A Global Mapping of Pediatric Radiologists and Pediatric Radiology Training

Authors:

Gloria Soto; Kara-Lee Pool; Cassandra Grageda; Amanda Dehaye; Hubert Ducou Le Pointe; Kath Halliday; Wendy Lam; Miguel A Lopez Pino; Hans-Joachim Mentzel; Gladys Mwango; Rutger Jan Nievelstein; Ines Boechat

WHO Standardized Chest X-Ray Interpretation

Standardized interpretation of paediatric chest radiographs for the diagnosis of pneumonia in epidemiological studies

Thomas Cherian,[1] E. Kim Mulholland,[2] John B. Carlin,[3] Harald Ostensen,[1] Ruhul Amin,[4] Margaret de Campo,[5] David Greenberg,[6] Rosanna Lagos,[7] Marilla Lucero,[8] Shabir A. Madhi,[9] Katherine L. O'Brien,[10] Steven Obaro,[11] Mark C. Steinhoff,[12] & the WHO Radiology Working Group

Background Although radiological pneumonia is used as an outcome measure in epidemiological studies, there is considerable variability in the interpretation of chest radiographs. A standardized method for identifying radiological pneumonia would facilitate comparison of the results of vaccine trials and epidemiological studies of pneumonia.
Methods A WHO working group developed definitions for radiological pneumonia. Inter-observer variability in categorizing a set of 222 chest radiographic images was measured by comparing the readings made by 20 radiologists and clinicians with a reference reading. Intra-observer variability was measured by comparing the initial readings of a randomly chosen subset of 100 radiographs with repeat readings made 8–30 days later.
Findings Of the 222 images, 208 were considered interpretable. The reference reading categorized 43% of these images as showing alveolar consolidation or pleural effusion (primary end-point pneumonia); the proportion thus categorized by each of the 20 readers ranged from 8% to 61%. Using the reference reading as the gold standard, 14 of the 20 readers had sensitivity and specificity of ≥ 0.70 in identifying primary end-point pneumonia; 13 out of 20 readers had a kappa index of > 0.6 compared with the reference reading. For the 92 radiographs deemed to be interpretable among the 100 images used for intra-observer variability, 19 out of 20 readers had a kappa index of > 0.6.
Conclusion Using standardized definitions and training, it is possible to achieve agreement in identifying radiological pneumonia, thus facilitating the comparison of results of epidemiological studies that use radiological pneumonia as an outcome.

Pediatr Radiol (2017) 47:1399–1404
DOI 10.1007/s00247-017-3834-9

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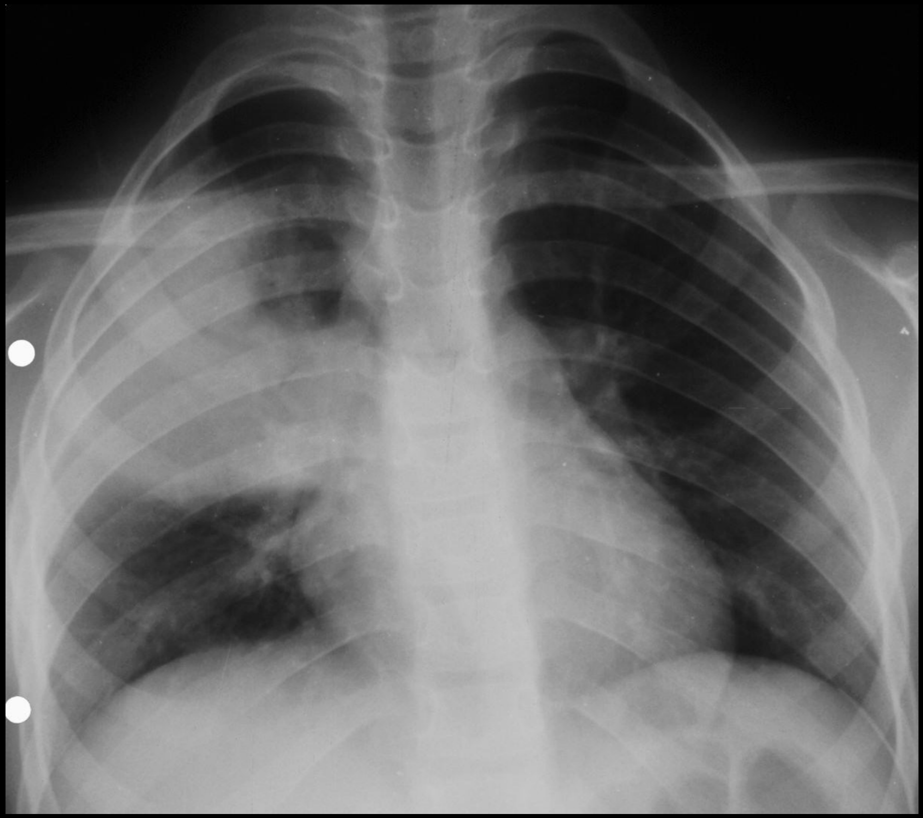
MINISYMPOSIUM: IMAGING PNEUMONIA

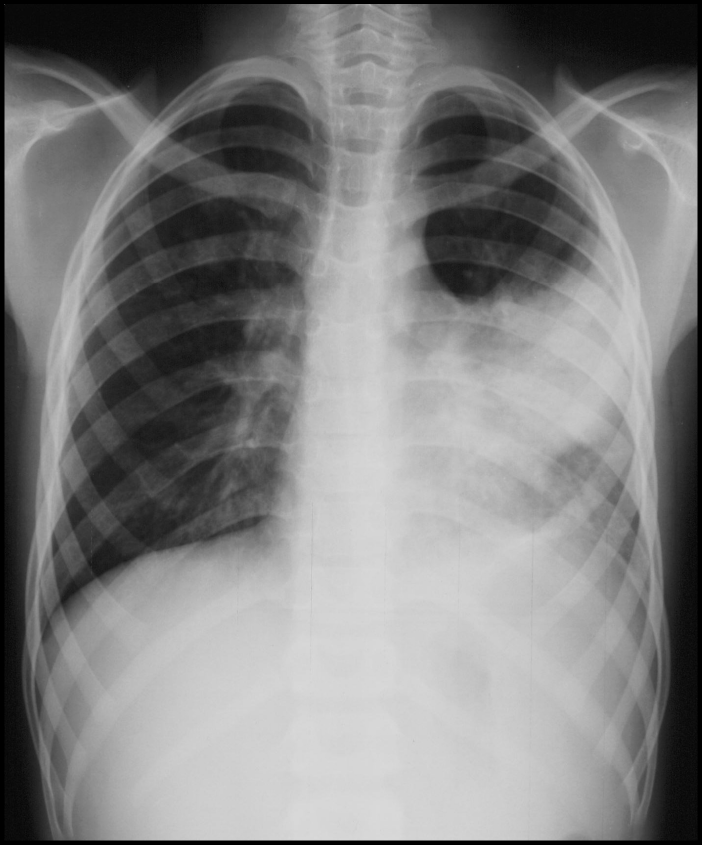
Preliminary report from the World Health Organisation Chest Radiography in Epidemiological Studies project

Nasreen Mahomed[1,2] · Nicholas Fancourt[3,4] · John de Campo[4,5] · Margaret de Campo[4,5] · Aliu Akano[6,7] · Thomas Cherian[8] · Olivia G. Cohen[3,8] · David Greenberg[9] · Stephen Lacey[4] · Neera Kohli[10] · Henrique M. Lederman[11] · Shabir A. Madhi[2,12] · Veronica Manduku[13] · Eric D. McCollum[14,3] · Kate Park[15] · Jose Luis Ribo-Aristizabal[16] · Naor Bar-Zeev[17,18] · Katherine L. O'Brien[3] · Kim Mulholland[4,19]

Received: 18 January 2017 / Accepted: 8 March 2017 / Published online: 20 September 2017

Abstract Childhood pneumonia is among the leading infectious causes of mortality in children younger than 5 years of age globally. *Streptococcus pneumoniae* (pneumococcus) is the leading infectious cause of childhood bacterial pneumonia. The diagnosis of childhood pneumonia remains a critical epidemiological task for monitoring vaccine and treatment program effects. The chest radiograph remains the most readily available and common imaging modality to assess childhood pneumonia. In 1997, the World Health Organization Radiology Working Group was established to provide a consensus method for the standardized definition for the interpretation of pediatric frontal chest radiographs, for use in bacterial vaccine efficacy trials in children. The definition was not designed for individual patient clinical management because of its emphasis on specificity at the expense of sensitivity. These definitions and endpoint conclusions were published in 2001 and an analysis of observer variation for these conclusions using a reference library of chest radiographs was published in 2005. In response to the technical needs identified through





Phase 1- CAD CXR

- Objective: To determine the sensitivity and specificity of CAD CXR-PEP for vs non CXR-PEP and CXR-PEP vs other infiltrate
- This study was nested within the PERCH study, South African site
- Majority consensus radiologist reading was used as the reference gold standard

The PERCH Study

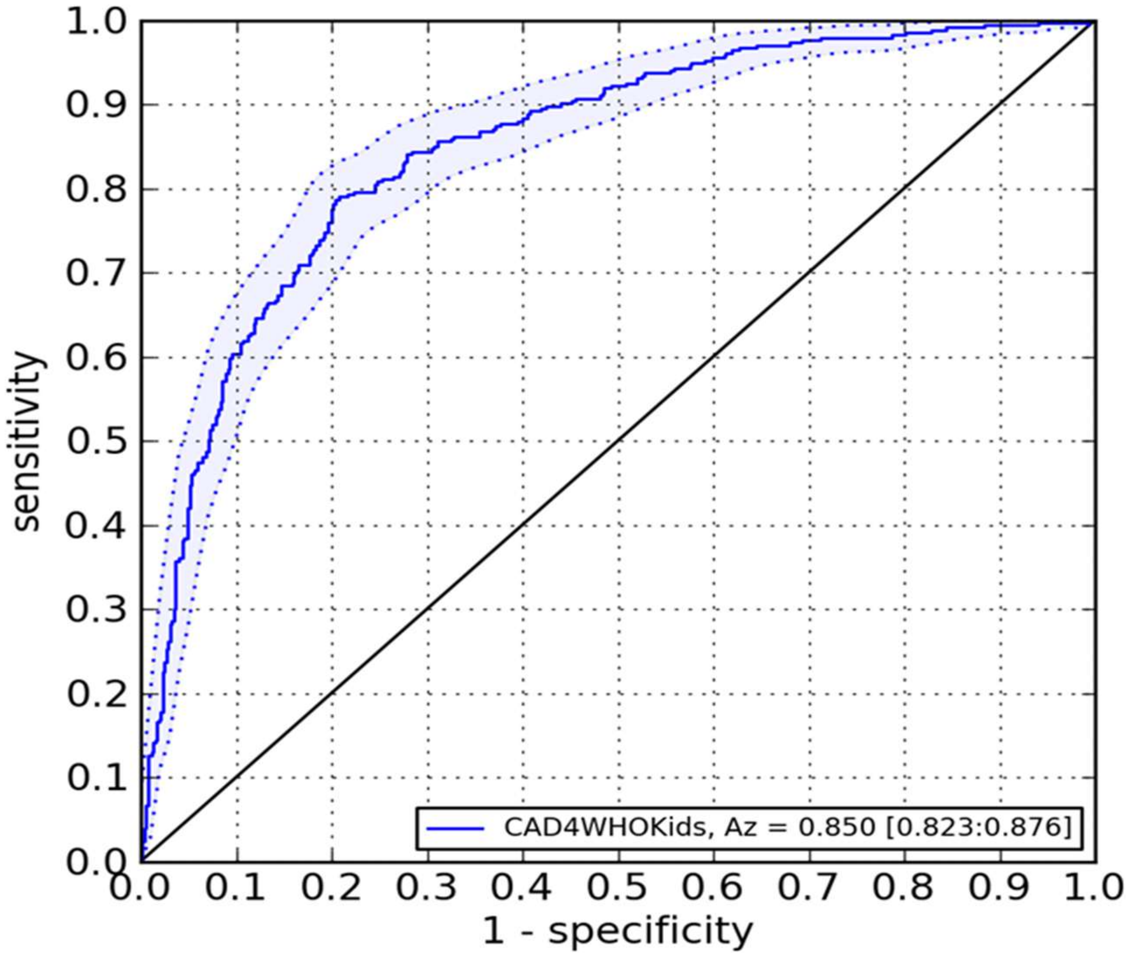
- Katherine L. O’Brien, Orin S. Levine, Maria Deloria Knoll and the PERCH study group. **Aetiology of severe hospitalised pneumonia in HIV-uninfected children from Africa and Asia: the Pneumonia Aetiology Research for Child Health (PERCH) Case-Control Study. The Lancet March 2019 online (impact factor 52.6)**

Methods- CAD4WHOKids

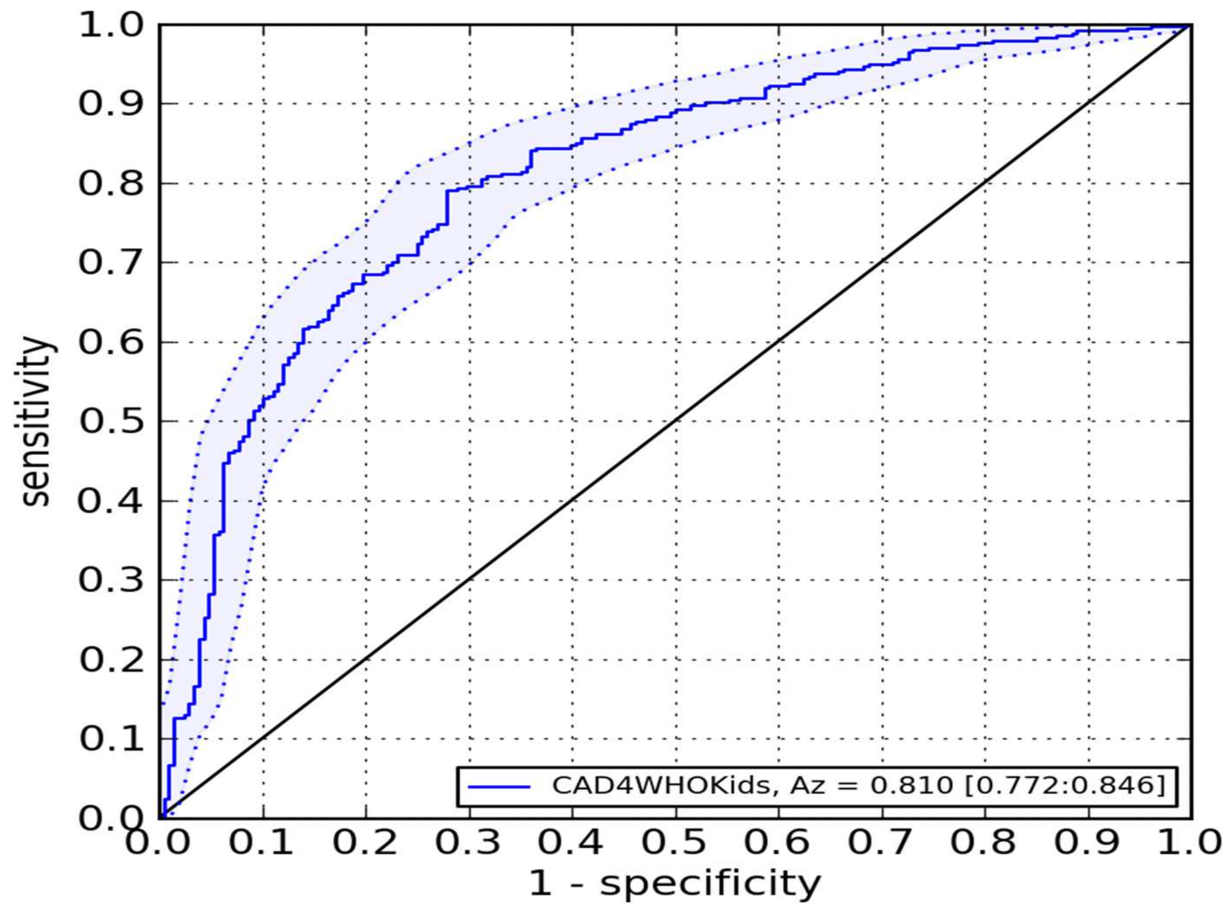
- **Automatic lung field segmentation** followed by manual inspection and correction
- **Training**- Pixels in outlined regions were used as positive examples, training and testing was done in 10-fold cross validation
- **Feature extraction**
- **Classification**- Pixel data was filtered with Gaussian derivatives on multiple scales, extracting texture features to classify each region
- To obtain an image score, the 95th percentile score of the pixels was used

Results- Phase 1 CAD CXR

- 858 interpretable chest X-rays
- 10-fold cross validation for the test set 85 CXRs were included- 10 times
- Lung fields were manually outlined in 25% (n=214) randomly selected chest X-rays
- Automatic lung field segmentation was used
- On manual inspection lung fields had to be manually corrected in **37%** (237/644)



For CXR-PEP versus non CXR-PEP, from 858 CXRs where 333 had CXR-PEP, CAD4WHOKids had a sensitivity of 76%, specificity of 80% and area under the **ROC curve of 0.850** (95% CI 0.823-0.876)



CXR-PEP vs other infiltrate only, where normal chest X-rays were excluded, from the 541 chest X-rays CAD4WHOKids had a sensitivity of 77%, specificity of 73%, and area under the **ROC curve of 0.810** (95% CI 0.772-0.846)

Results- Colour Heat Map

- To visualise the working of the texture system, for each image a colour heat map was generated with red representing high likelihood of being abnormal, yellow intermediate, green low, and blue very low

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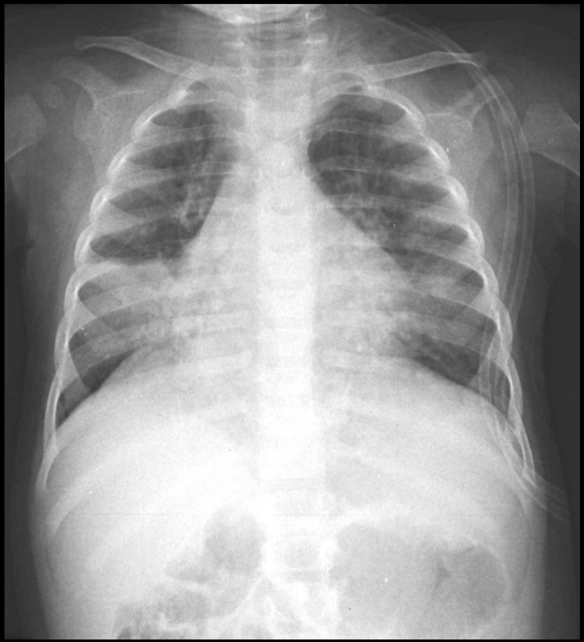
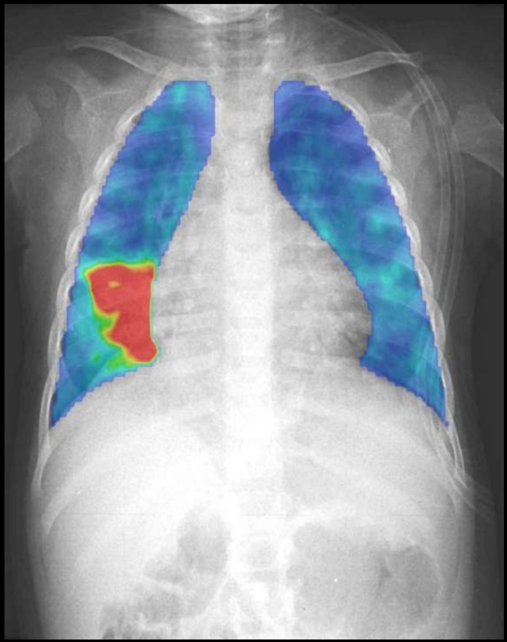
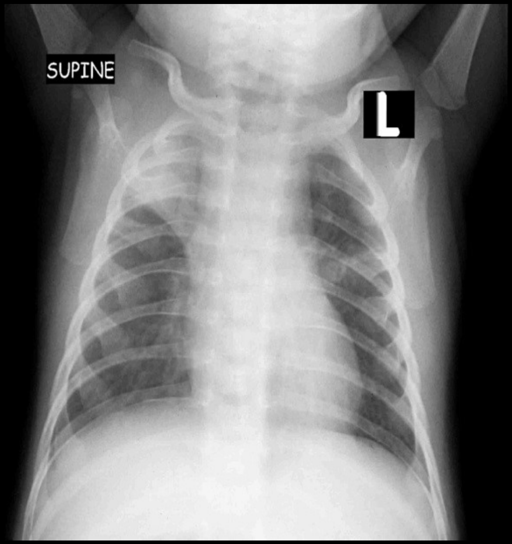
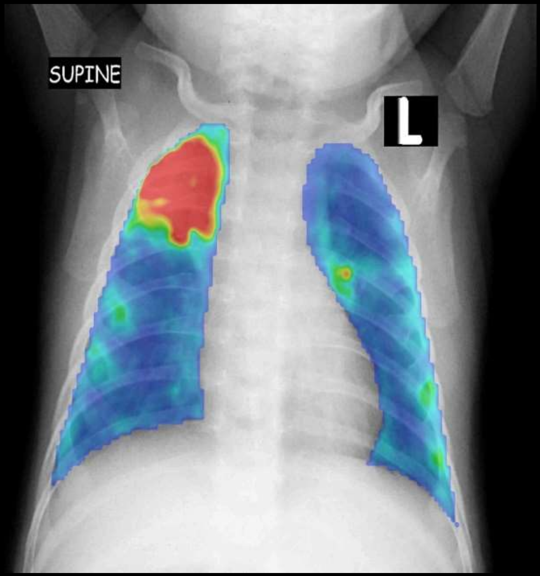








Phase 2 – Convolutional neural networks

- Objective: To determine the sensitivity and specificity of CAD for:
  - CXR-PEP vs non-CXR-PEP
- Setting: multi-centre study in South Africa
- Majority consensus reading based on WHO criteria was used as the reference gold standard

Phase 2 - Methods

- Automated lung segmentation using deep learning architecture
- A combination of of-the-shelf “google-net” and custom deep convolutional neural networks were trained and evaluated for differentiating between CXR-PEP and non-CXR-PEP

Phase 2 - Methods

- This study was nested within hospitalized South African children with pneumonia in the PERCH study and the PCV-13 study
- 4 Datasets:
  - PERCH (Pneumonia Etiology Research in Child Health)
  - CHBAH (Chris Hani-Baragwanath Academic Hospital)
  - NGWE (Ngwelezane Hospital)
  - RCCH (Red Cross War Memorial Children's Hospital)

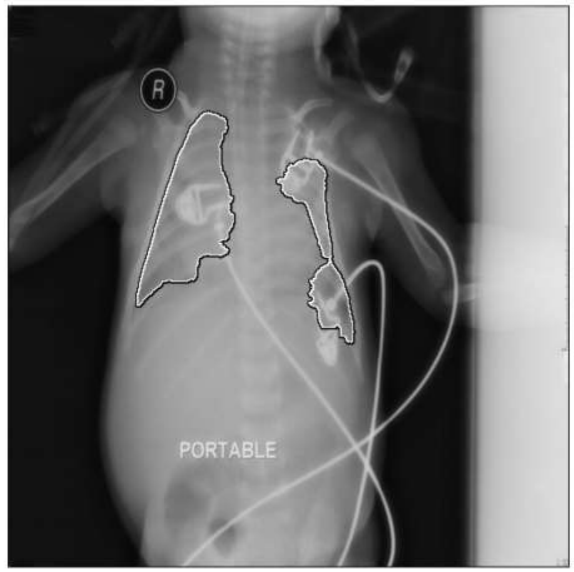
Phase 2 - Methods

	Total	Training	Validation	Test
PERCH	858	730	128	
CHBAH*	1465	641	112	200
NGWE	379	152	27	200
RCCH	903	598	105	200

* 512 images were not used

Results- Jaccard Index

(a)

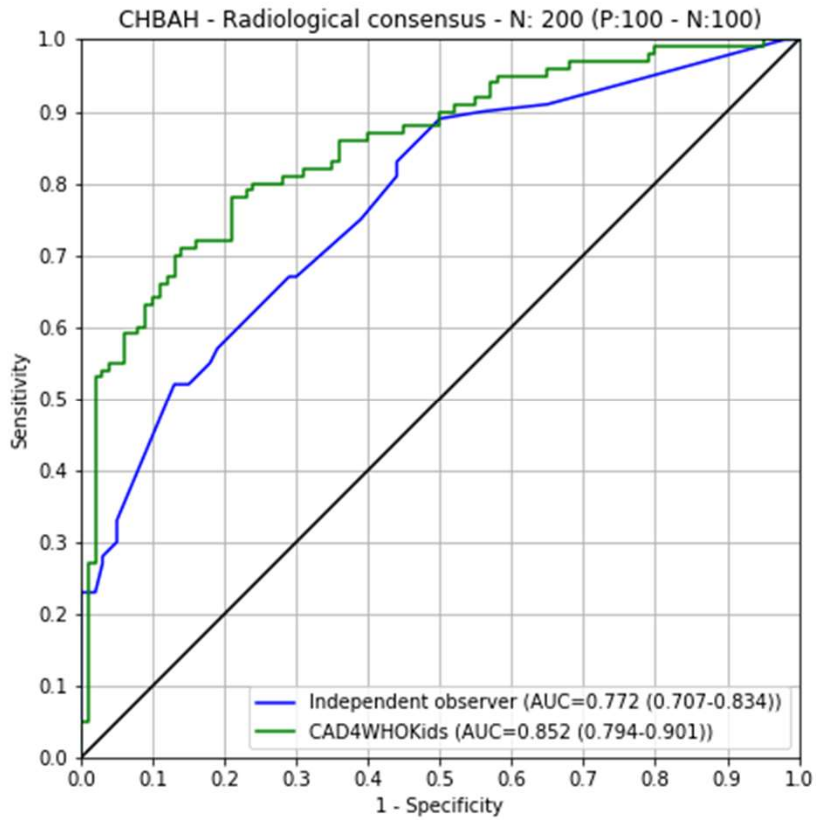


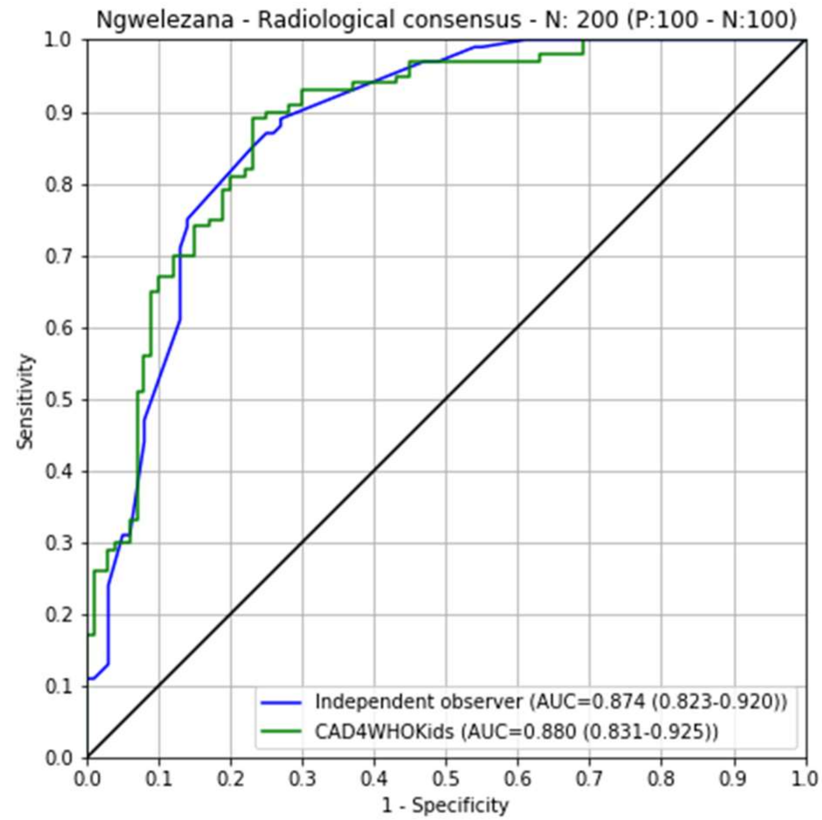
(b)

(c)

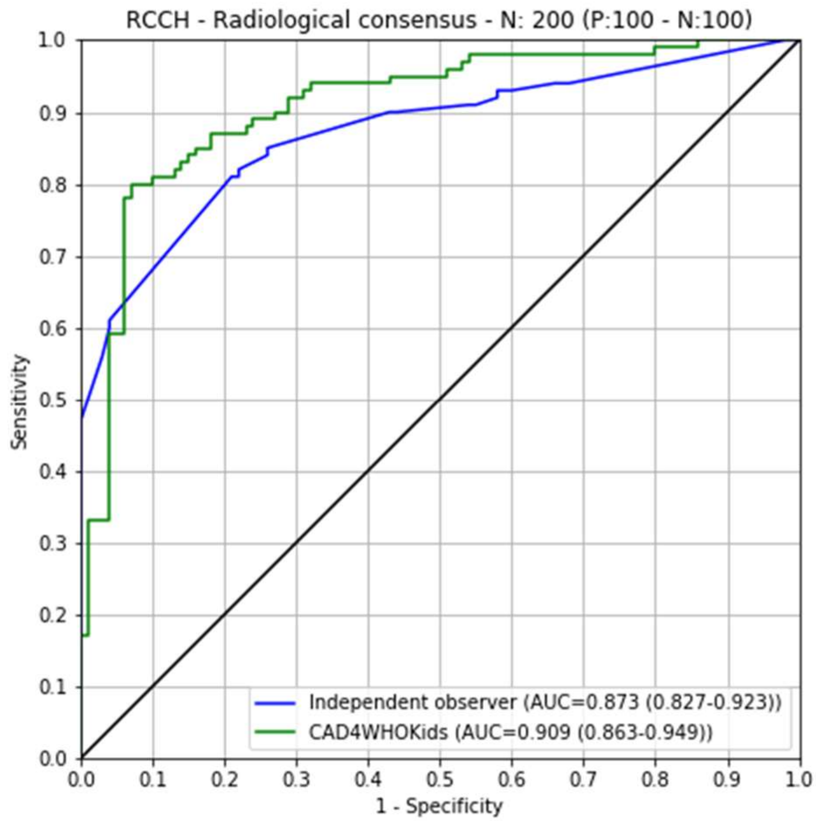
- **Average Jaccard Index: 0.928**
- Best segmentation: 0.973 (a)
- Worst segmentation: 0.532 (b)
- Difficult segmentation: 0.964 (c)

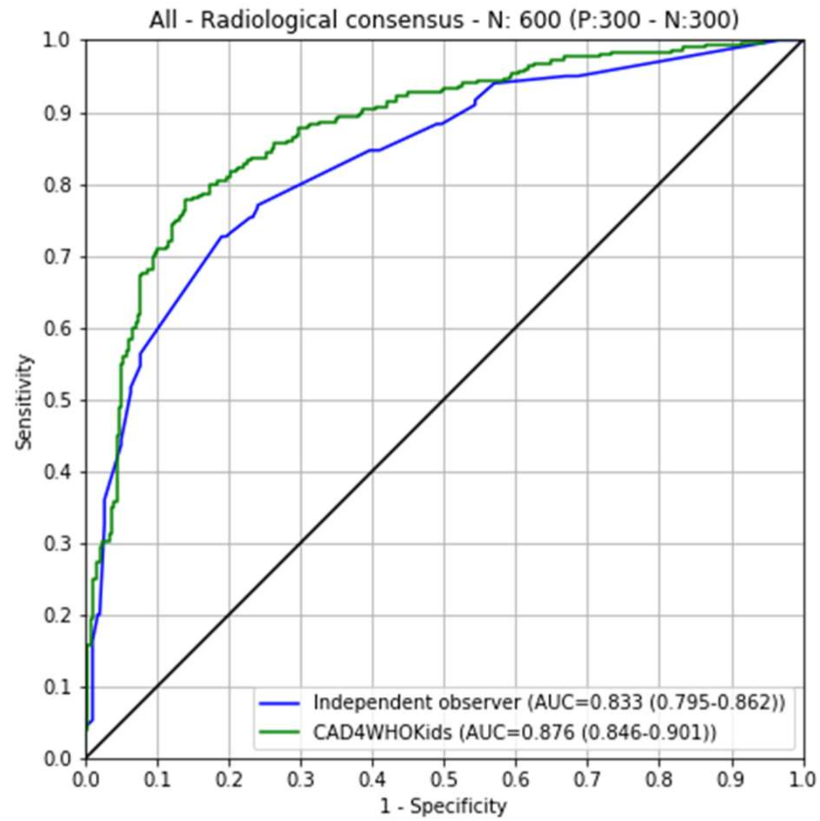
Phase 2 - Results





Phase 2 - Results





Phase 2 - Results

- Performance improvements compared to phase 1
- More sophisticated deep learning methods are used
- Fully automated lung segmentation-JI
- AUC values:
  - CAD4WHOKids: **0.876** (95% CI: 0.846-0.901)

Limitations

- JPEG images instead of Diacomm less data
- CXR quality was often limited:
  - Poor collimation
  - Rotation
  - Motion artefact
  - Foreign objects in chest X-rays (ECG leads)

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Discussion CAD for CXR Pneumonia in Children

- Oliveira et al Pneumo-CAD sensitivity of 100%, specificity of 80% and area under the ROC curve of 0.97
- This study was limited by small sample size of **60** children
- Poor CXR quality as CXRs were photographed from a light box using a digital camera which is not advised according to the WHO standardized CXR interpretation criteria, low image quality

Oliveira LL, Silva SA, Ribeiro LH, et al. Computer-aided diagnosis in chest radiography for detection of childhood pneumonia. Int J Med Inform. 2008 Aug;77(8):555-64.

Conclusion and Future Research

- CAD4WHOKids texture analysis is promising for identifying WHO CXR-PEP in children
- Important to evaluate the software against the new WHO clarifications and a radiological gold standard like CT chest
- Phase 3: evaluate CAD4WHOKids on a large international multi-centre study PERCH 7 countries: Bangladesh, The Gambia, Kenya, Mali, South Africa, Thailand and Zambia to assess its performance

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Acknowledgments

- International collaborators on CAD CXR Diagnostic Image Analysis Group- Nijmegen, Netherlands- Philipsen R, Melendez J, **Van Ginneken B**
- WHO Chest Radiography in Epidemiological Studies (CRES) project
- MRC Respiratory and Meningeal Pathogens Research Unit (RMPRU)- Moore D, Groome M, Madhi S A