

Case study: Al for pneumonia detection in low resource settings





Part 2: Case study









Artificial Intelligence

Machine learning

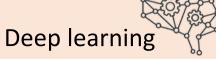


Supervised



Unsupervised





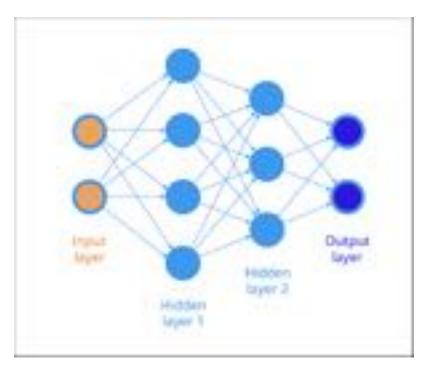


Machine learning Deep learning





- Based on artificial neural networks
- Processing happens over multiple layers
- Used to extract high level information
- Can be supervised or unsupervised

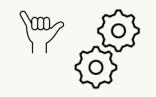


https://machinelearningmastery.com/calculus-in-action-neural-networks/



Machine learning

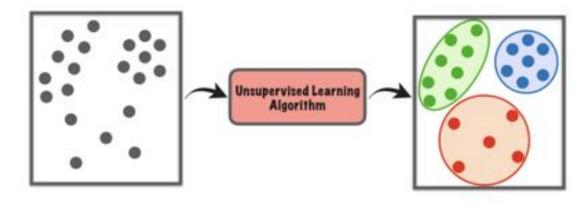
Unsupervised Learning





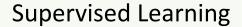
- Unlabelled data
- Identify 'hidden' unknown patterns in data
- Example:

Are there patterns in the data to indicate whether certain patients respond better to the treatment?





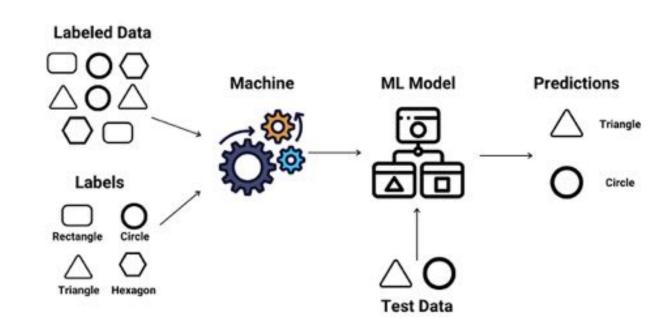
Machine learning







- Labelled data
- Classification/ regression problems
- Algorithms learn based on accuracy of predictions





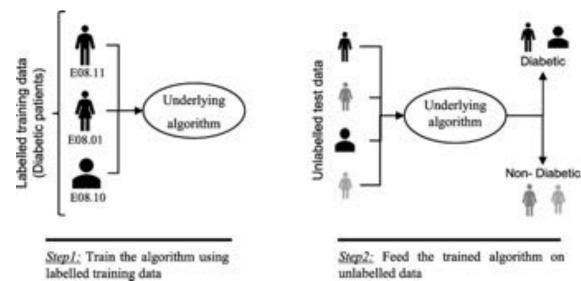
Machine learning Supervised Learning





- Labelled data
- Classification/regression
 n problems
- Algorithms learn based on accuracy of predictions

Example: Diagnose diseases using a trained ML algorithm



Uddin, S., Khan, A., Hossain, M. *et al.* Comparing different supervised machine learning algorithms for disease prediction. *BMC Med Inform Decis Mak* **19**, 281 (2019). https://doi.org/10.1186/s12911-019-1004-8







Artificial Intelligence

Data!

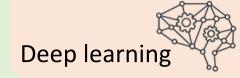
Machine learning



Supervised



Unsupervised



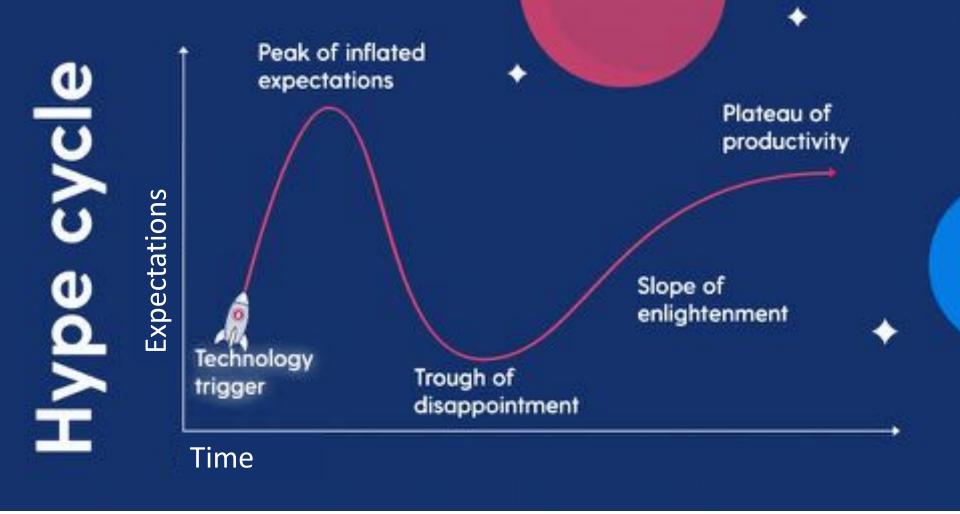


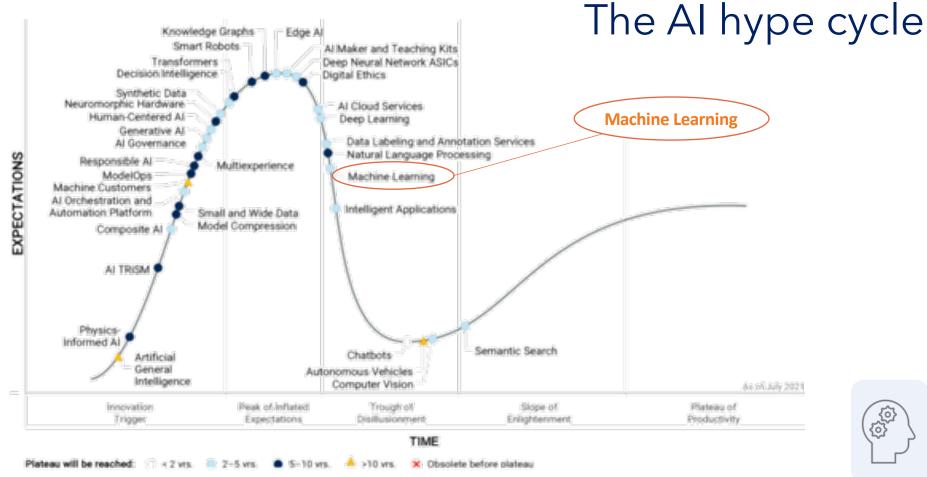
People that say that AI will take over the world:

My own Al:



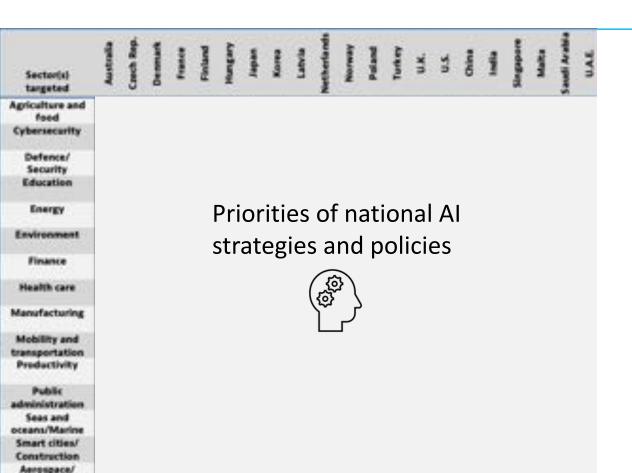








Source: Gartner (September 2021), https://www.gartner.com/en/documents/3887767





Which sectors do most countries target with Al policies?
Why?



Telecomms and IT

	Sector(s) targeted	Australia	Crech Rep.	Denmark	France	Finland	Hugary	Japan	Korea	Labria	Netherlands	Norway	Poland	Turkey	ux.	0.5	China	ă	Singapore	Maffe	Saudi Arabia	UAE	
	Agriculture and feed	1	110	4			1	4	1	1	1		1	1	gu.	4	4	1		600		115	WARWICK
	Cybersecurity							×					4	1			m		1				THE UNIVERSITY OF WARWICK
	Defence/			П	5				1	1	Г	П		1	П	V.	1		1	П	П	5	
	Security Education		1				1	V	1					1		V	ì	V	1	1			
	Energy			V		7	1			1	1	1	1		v	v	V.			1	1	1	
	Environment	4			4		1				8				4	4					*		
\ \ \	Finance			Г				П	1	1		Г	Г				П		1				
	Health care	1	1	1	7	V	1	1	Z	2	V	1	V	1	1	1	1	1	1	1	1	1	> کالیا
)	Manufacturing						7	7	4					1	4	4.					¥		\sim
	Mobility and		1	1	1	1	1	7		4	8	1	1	7	4	7	3	1	1	7	8	1	
	transportation Productivity					1		4				-	1	1			1000						
	Public administration				V	1	1	V	1	4		7	4	1						1		B	
	Seas and oceans/Marine			Г	П			П	1	4		1	Г	П	П		П			П		П	
	Smart cities/ Construction	1								1			1	1				1			3	1	
	Aerospace/ Space		1						1							V							
	Telecomms and IT							4	1	-				*	111	Y				4			

OECD.AI (2021), powered by EC/OECD (2021), database of national AI policies, accessed on 2/08/2022, https://oecd.ai

Al for healthcare



Think of some different ways AI can be applied to healthcare





Some ideas:



Mobile health

Health informatics

Decision support systems

Diagnostics

Healthcare management



The role of AI:

Learning from data, prediction vs detection





Predict event/condition -> prevent



Detect event/condition -> mitigate

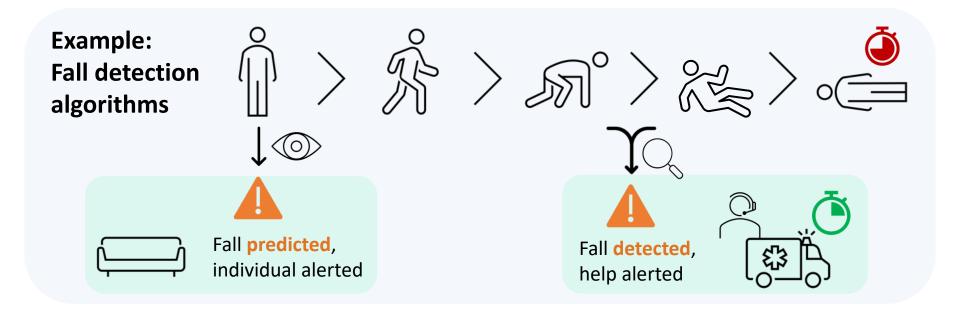
The role of AI:

Learning from data, prediction vs detection



Predict event/condition -> prevent

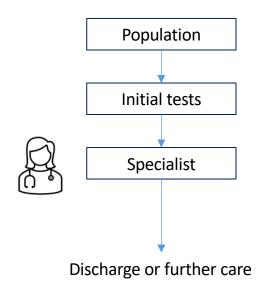
Detect event/condition -> mitigate



Al and the clinical workflow

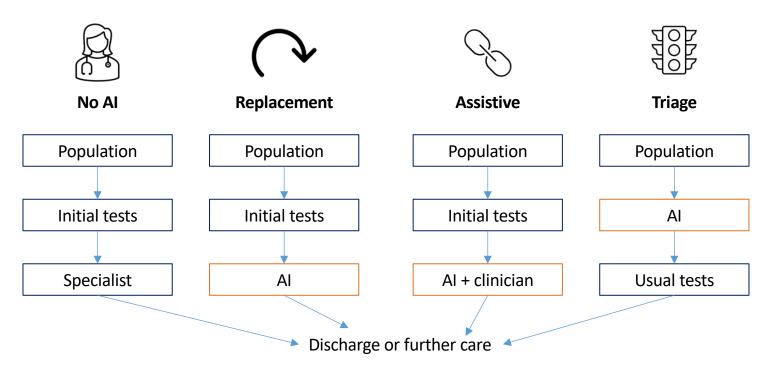


Example care pathway



Al and the clinical workflow



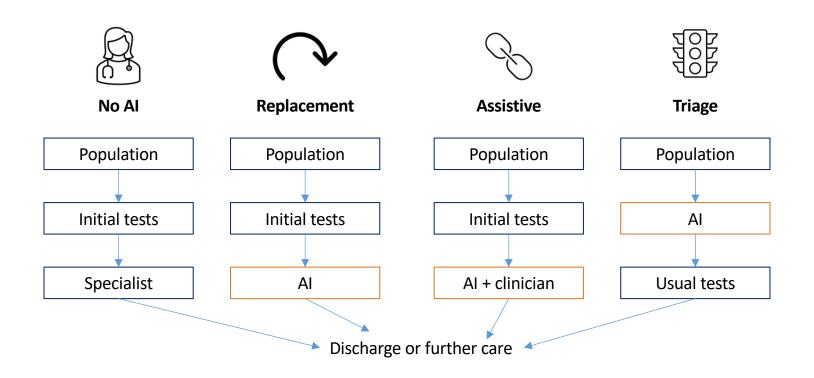




Breakout discussion

What are the different factors that you would need to consider for the different approaches?

What are the different factors that you would need to consider for the different approaches?



A few ideas...





- **Replacement**: how can you ensure that previous standards will be met? Will the validation process be the same?

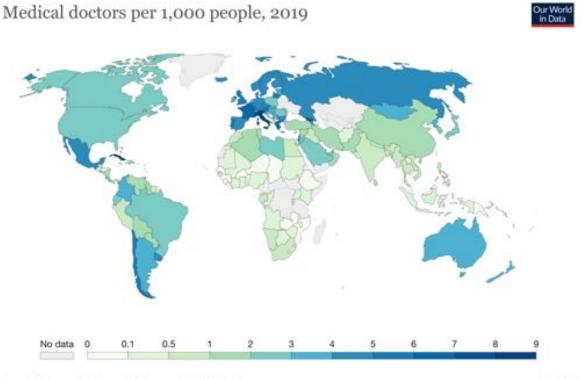


- **Assistive**: How interpretable do the results need to be?
 - Can the system direct a healthcare workers attention to particular factors?



- **Triage**: will data be consistent across individuals?
 - o Can you build flexibility into the system?

Al for healthcare: low-resource settings



Motivations:

- Shortage of healthcare personnel, resources and tests
- Healthcare cost
- Disease burden

Al for healthcare: low-resource settings

Challenges to AI implementation

- Availability of high quality training data
- Infrastructure
 - Power
 - Network
- Digital literacy
- Regulatory and policy frameworks







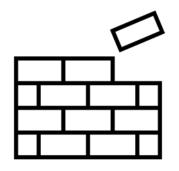
Al for healthcare in low-resource settings, where are we?



- Research: little evidence in academic literature
- Industry: over half of the global medical device market held by the US and Europe.
- Policy: relatively few policy initiatives

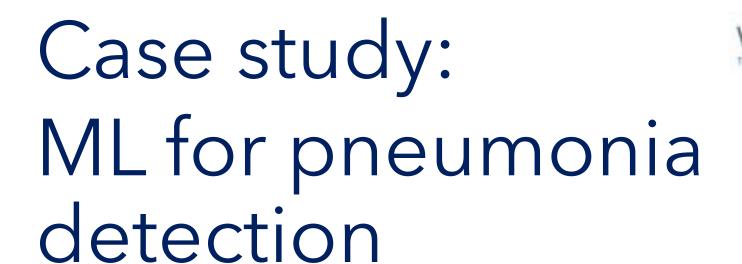


Al for healthcare in lowresource settings; important considerations





- Clear definition of the healthcare problem to be addressed
- Inclusivity for local populations
- Sustainability for development and maintenance of medical technologies
- Regulatory and legal strategies for reliability

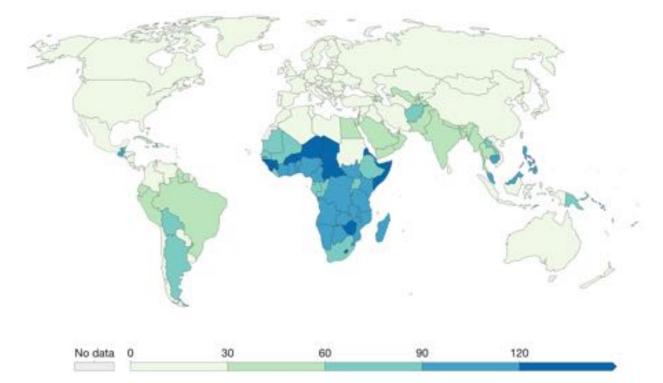


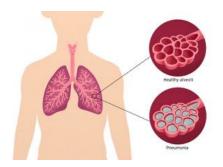
Death rate from pneumonia, 2019

The annual number of deaths from pneumonia per 100,000 people.









SUSTAINABLE GOALS



























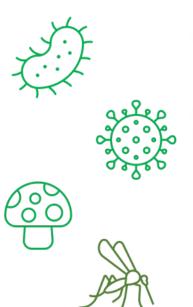


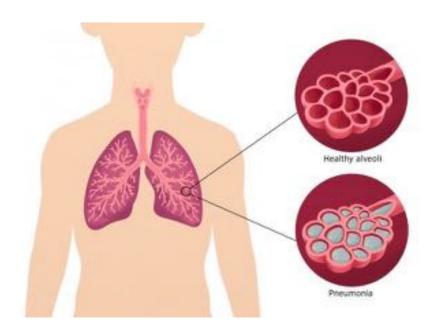




Introduction

Pneumonia etiology





















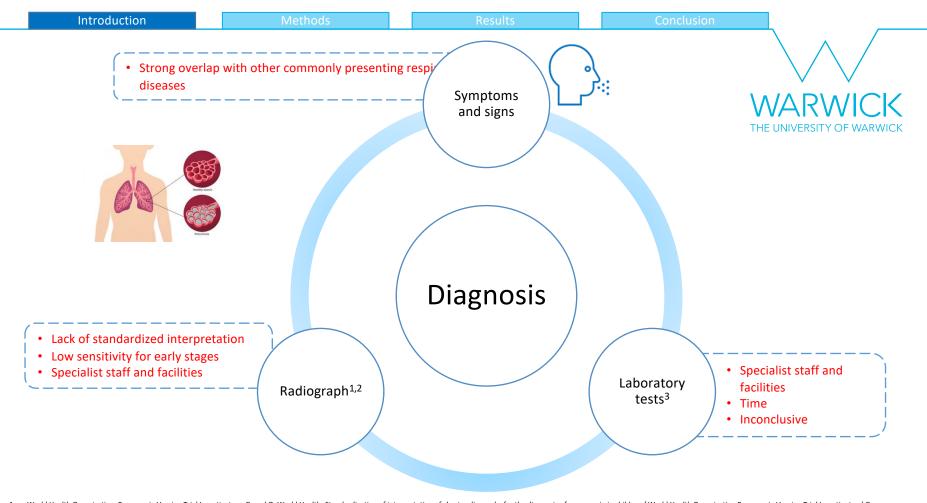








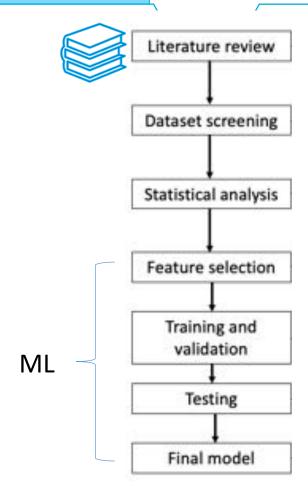




- 1. World Health Organization. Pneumonia Vaccine Trial Investigators, G. and O. World Health, Standardization of interpretation of chest radiographs for the diagnosis of pneumonia in children / World Health Organization Pneumonia Vaccine Trial Investigators' Group. 2001, World Health Organization: Geneva.
- Garber, M.D. and R.A. Quinonez, Chest Radiograph for Childhood Pneumonia: Good, but Not Good Enough. Pediatrics, 2018. 142(3): p. e20182025.
- Principi, N. and S. Esposito, Biomarkers in Pediatric Community-Acquired Pneumonia. International journal of molecular sciences, 2017. 18(2): p. 447.

Methods

- Finding the evidence: Systematic literature review
 - Type of pneumonia
 - Study design and subject population
- Machine Learning (ML) methods and performance



Review: Finding the evidence and informing ML methods



Identify most used symptomatic predictors

Identify models frequently used

Lack of clarity in type and diagnosis of pneumonia

Unclear reporting of methods and performance

Lack of studies distinguishing pneumonia from other respiratory diseases

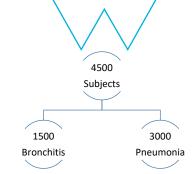


Commonly used symptomatic predictors:

- Fever/temperature
- · abnormal breathing
- cough
- productive cough
- dyspnoea
- absence of runny nose
- chest in drawing

The dataset

Bosnia and Herzegovina, low-middle-income country



Population descriptive

- Age
- Sex
- Exposure to air pollution
- Malnutrition
- Immunosuppression
- Allergy
- Associated diseases



Symptomatic

- Cough
- Expectoration
- Dyspnoea
- Pleura pain
- Temperature
- Fever
- Sweating
- Muscle pain
- Headache
- Loss of appetite
- Sputum
- Auscultation

Laboratory tests

- Sedimentation
- Fibrinogen
- CRP
- Leukocytes
- Neutrophils
- Lymphocytes
- Monocytes
- Basophils
- Eosinophils
- Spirometry



Machine Learning methods

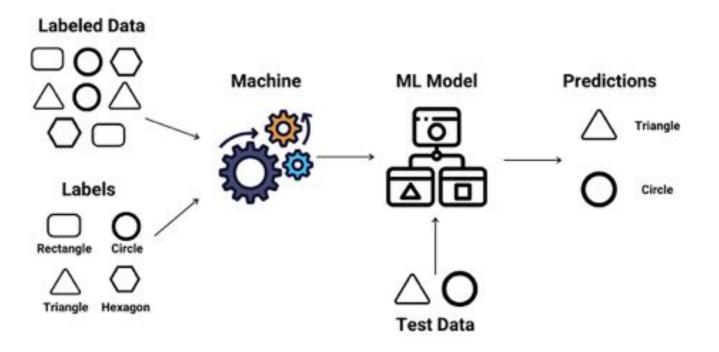
Using symptoms/signs as predictors

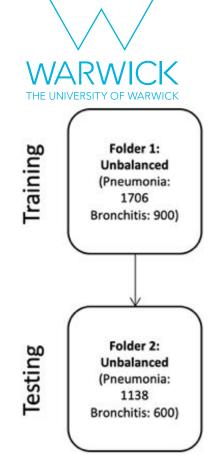




- Decision tree: Set of 'if-else' conditions to predict class of a given case
 - Simple, interpretable
- Logistic regression: Simple finds equation with coefficients for predictors and an intercept
 - Simple, interpretable
- Linear Support Vector Machine (SVM): Seeks to find optimum hyperplane giving best separation of variables
 - 'Black-box'

Building a Machine Learning model: Training and testing



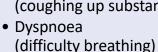


Machine Learning model: best predictors

- Manual approach
 - Only considering variables measurable in low resource setting
- Several symptoms excluded as they were not reported for bronchitis patients
- Addition of population descriptive variables did not improve performance



- Cough
- Expectoration (coughing up substances)



- Pleura pain (chest pain)
- Temperature
- Fever
- Sweating
- Muscle pain
- Headache
- Loss of appetite
- Sputum (lung mucus inspection)
- Auscultation

Evaluating performance

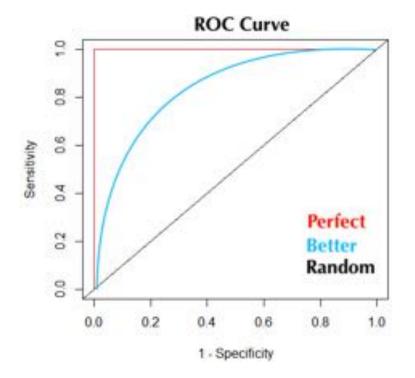


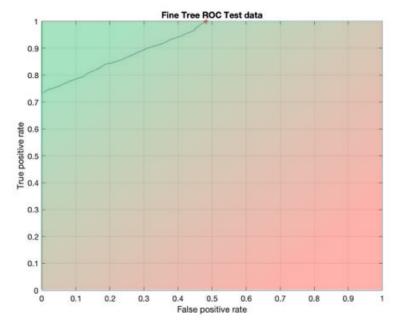
Method	AUC	Sensitivity	Specificity
Decision Tree	93%	81%	84%
SVM	93%	78%	86%
LR	93%	73%	88%

- Comparable with results of literature review
- Good interpretability of final model

Evaluating performance







Conclusion



• Future work:

- Verify/validate model using data form low-income countries/populations with high pneumonia burden
- Inclusion of additional commonly co-presenting respiratory diseases
- Explore improvements in performance
 - Incorporation of sensor readings: e.g., cough sounds, temperature reading

• Limitations:

- Only distinguishing 2 respiratory diseases
- No information on type of pneumonia or diagnosis criteria
- Some symptoms not measurable by all healthcare workers such as auscultation

Acknowledgements/ publications



- Rosanna Castaldo and Leandro Pecchia (supervision)
- Lejla Gurbeta Pokvic, Almir Badnjevic (data)
- Stokes K, Castaldo R, Federici C, et al. The use of artificial intelligence systems in diagnosis of pneumonia via signs and symptoms: A systematic review. *Biomedical Signal Processing and Control* 2022;72:103325. doi: https://doi.org/10.1016/j.bspc.2021.103325
- Stokes K, Castaldo R, Franzese M, et al. A machine learning model for supporting symptom-based referral and diagnosis of bronchitis and pneumonia in limited resource settings. *Biocybernetics and Biomedical Engineering* 2021;41(4):1288-302.

doi: https://doi.org/10.1016/j.bbe.2021.09.002

Questions/discussion

