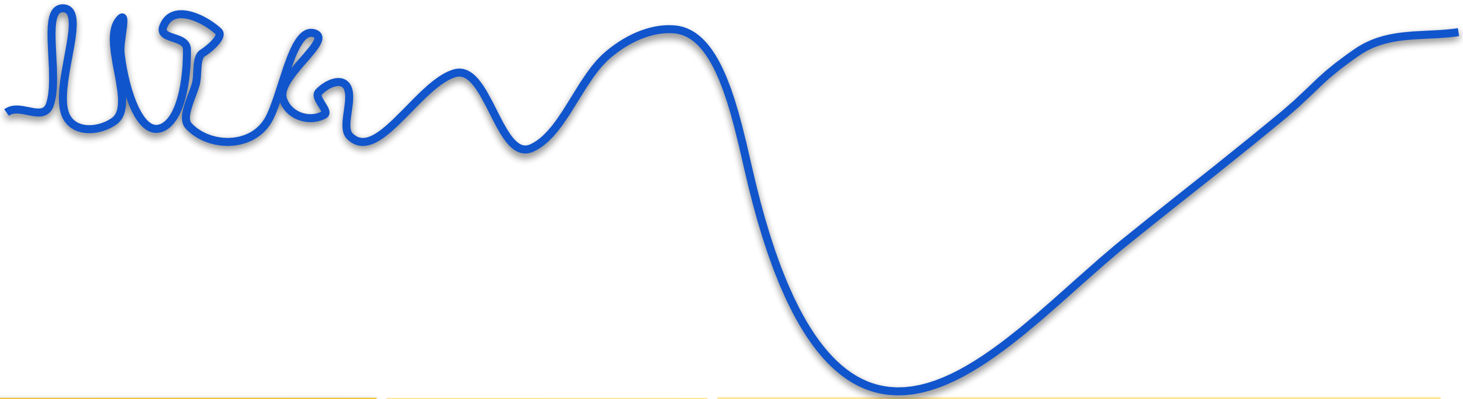
Computing with Signals



DA 623

Jan - May 2024

IIT Guwahati

Instructors: Neeraj Sharma

Lecture-05_06

Tour into Datasets

Datasets

- machine learning models are only as good as the data they’re trained on
- “garbage in, garbage out”
- “bias in, bias out”

Datasets

- machine learning models are only as good as the data they’re trained on
- “garbage in, garbage out”
- “bias in, bias out”

Yet, significance of data for machine learning is a lot more!

Datasets

Serves many other vital functions in the machine learning ecosystem

- The dataset itself is an integral part of the problem formulation
    - It implicitly sorts out and operationalizes what the problem is that practitioners end up solving

- Datasets have also shaped the course of entire scientific communities in their capacity to measure and benchmark:
    - Progress
    - Support competitions
    - Interface between researchers in academia & practitioners in industry

Datasets

There is no simple answer to the question of what makes data good for what purpose.

The collection of data for machine learning applications has not followed any established theoretical framework, certainly not one that was recognized a priori.

Datasets

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Let's look at some datasets which have shaped ML

TIMIT

- Texas Instruments/Massachusetts Institute for Technology (TIMIT) dataset
- The creation of the dataset was funded through a 1986 DARPA program on speech recognition
- In the mid-eighties, artificial intelligence was in the middle of a "funding winter"
- DARPA program manager Charles Wayne enlisted the National Institute of Standards and Technology to create and curate shared datasets for speech
- He graded success in his program based on performance on recognition tasks on these datasets

TIMIT features a total of about 5 hours of speech

- composed of 6300 utterances
- 10 sentences spoken by each of 630 speakers
- Sentences drawn from a corpus of 2342 sentences such as the following.

```
She had your dark suit in greasy wash water all year. (sa1)
Don’t ask me to carry an oily rag like that. (sa2)
This was easy for us. (sx3)
Jane may earn more money by working hard. (sx4)
She is thinner than I am. (sx5)
Bright sunshine shimmers on the ocean. (sx6)
Nothing is as offensive as innocence. (sx7)
```

Table 1: Demographic information about the TIMIT speakers

	Male	Female	Total (%)
White	402	176	578 (91.7%)
Black	15	11	26 (4.1%)
American Indian	2	0	2 (0.3%)
Spanish-American	2	0	2 (0.3%)
Oriental	3	0	3 (0.5%)
Unknown	12	5	17 (2.6%)

Table 1: Demographic information about the TIMIT speakers

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It comes to no surprise that early speech recognition models had significant demographic and racial biases in their performance.

English Tasks	WER%
LibriSpeech audiobooks 960hour clean	1.4
LibriSpeech audiobooks 960hour other	2.6
Switchboard telephone conversations between strangers	5.8
CALLHOME telephone conversations between family	11.0
Sociolinguistic interviews, CORAAL (AAL)	27.0
CHiMe5 dinner parties with body-worn microphones	47.9
CHiMe5 dinner parties with distant microphones	81.3

UCI Machine Learning Repository

- Currently hosts more than 500 datasets
- Mostly for different classification and regression tasks
- Most datasets are relatively small, consisting of a few hundred or a few thousand instances
- The majority are structured tabular data sets with a handful or a few tens of attributes

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The UCI Machine Learning Repository contributed to the adoption of the train-test paradigm in machine learning in the late 1980s.

UCI Machine Learning Repository

- The most popular dataset in the repository
  - Iris Data Set
  - Taxonomic measurements of 150 iris flowers, 50 from each of 3 species
  - The task is to classify the species given the measurements.
  - https://en.wikipedia.org/wiki/Iris_flower_data_set

- The second most popular dataset in the repository
  - Adult dataset
  - Extracted from the 1994 Census database
  - Features nearly 50,000 instances describing individuals in the United States, each having 14 attributes

MNIST Dataset

- The MNIST dataset contains images of handwritten digits
- Its most common version has 60,000 training images and 10,000 test images
- Each images has 28x28 black and white pixels

Figure 1: A sample of MNIST digits

MNIST Dataset

- MNIST was created by researchers Burges, Cortes, and Lecun from an earlier dataset released by the National Institute of Standards and Technology (NIST).

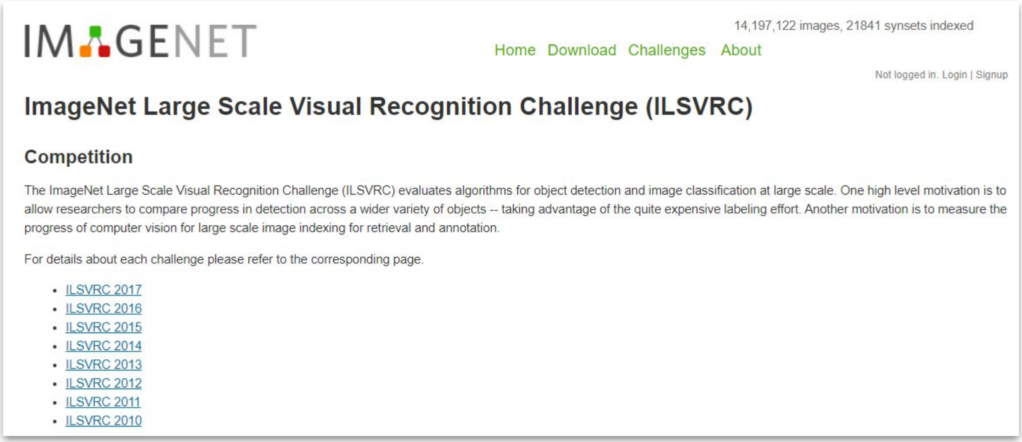
- Introduced in a research paper in 1998 to showcase the use of gradient-based deep learning methods for document recognition tasks.

- Cited over 30,000 times, MNIST became a highly influential benchmark in the computer vision community

ImageNet Dataset

- ImageNet is a large repository of labeled images that has been highly influential in computer vision research over the last decade

- The image labels correspond to nouns from the WordNet lexical database of the English language



A dataset we created

scientific **data**

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nature › scientific data › data descriptors › article

Data Descriptor | Open access | Published: 22 June 2023

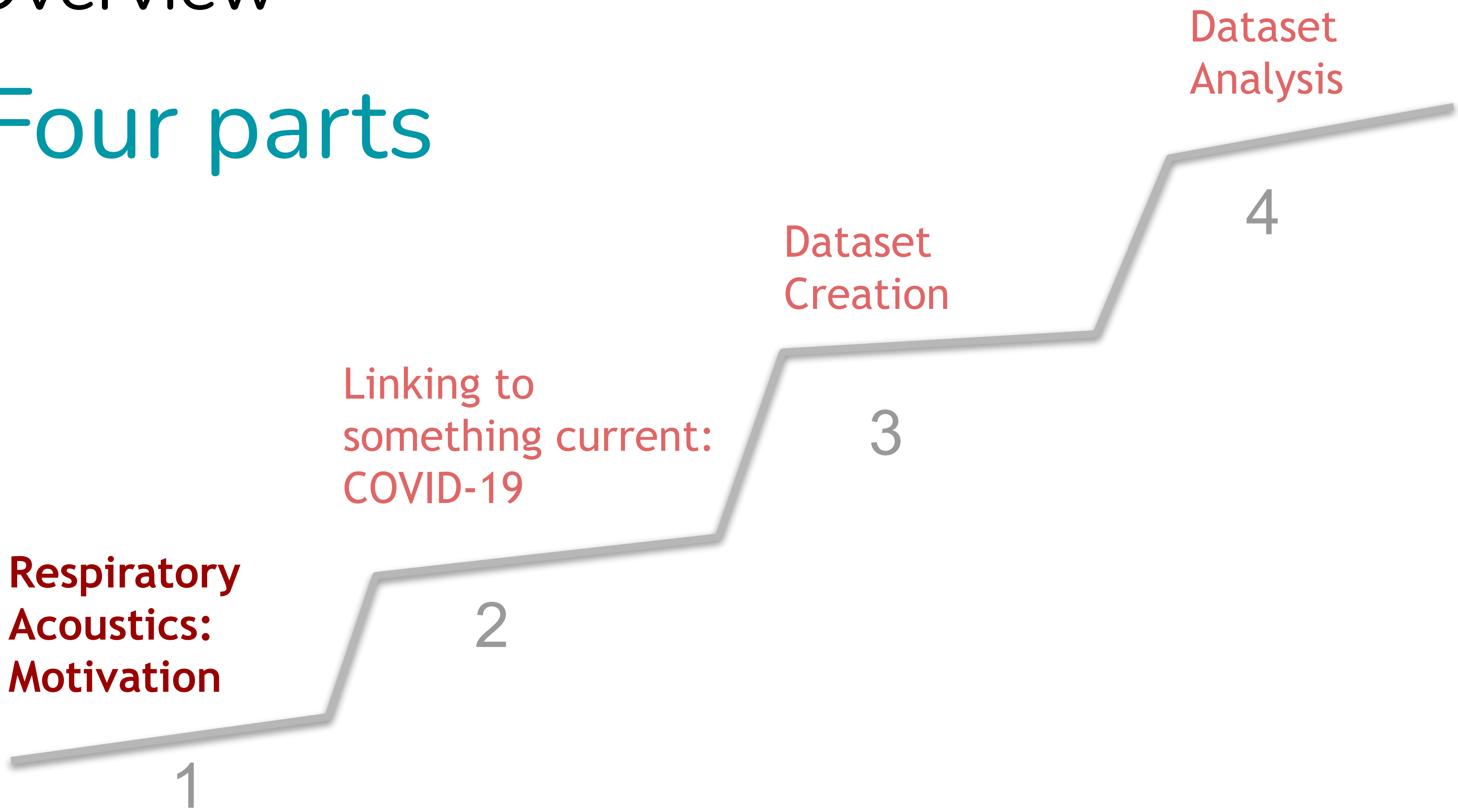
Coswara: A respiratory sounds and symptoms dataset for remote screening of SARS-CoV-2 infection

Debarpan Bhattacharya, Neeraj Kumar Sharma, Debottam Dutta, Srikanth Raj Chetupalli, Pravin Mote, Sriram Ganapathy ✉, C. Chandrakiran, Sahiti Nori, K. K. Suhail, Sadhana Gonuguntla & Murali Alagesan

Scientific Data **10**, Article number: 397 (2023) | Cite this article

Overview

Four parts



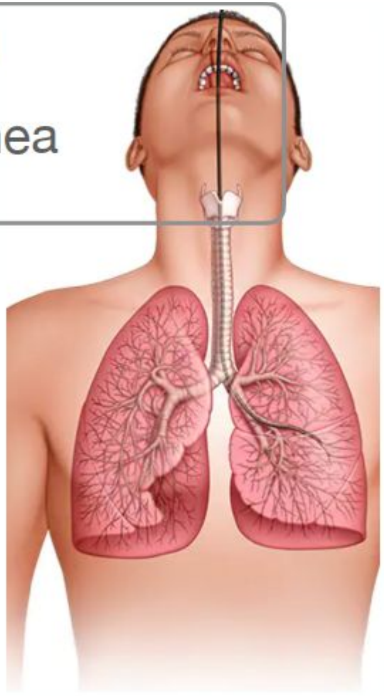
Respiratory System

- Upper respiratory tract
- Lower respiratory tract

Respiratory System

- Upper respiratory tract
- Lower respiratory tract

- nose, mouth, sinus
- throat, larynx, trachea

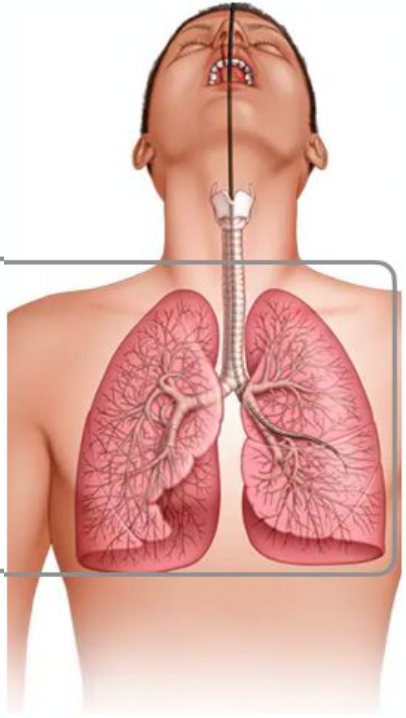


Courtesy: Mayo Foundation for Medical Education an

Respiratory System

- Upper respiratory tract
- Lower respiratory tract

- bronchial tubes
- lungs



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Respiratory System

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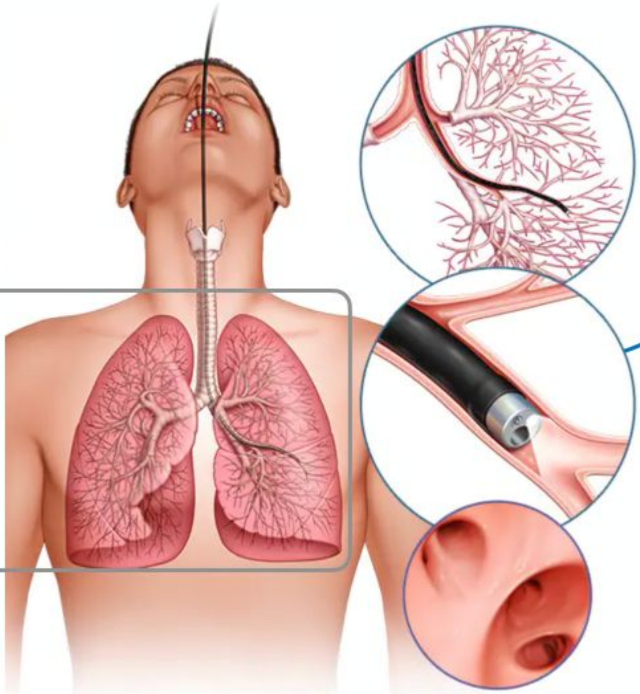
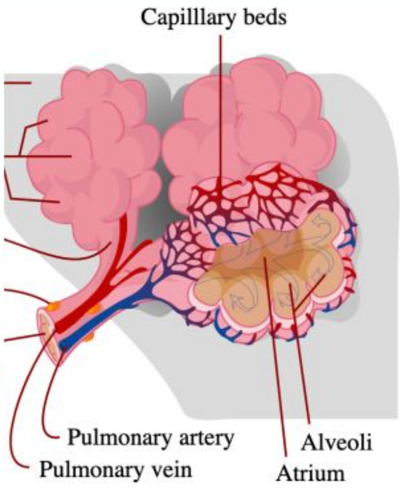


Courtesy: Mayo Foundation for Medical Education and Research



Courtesy: Wikipedia

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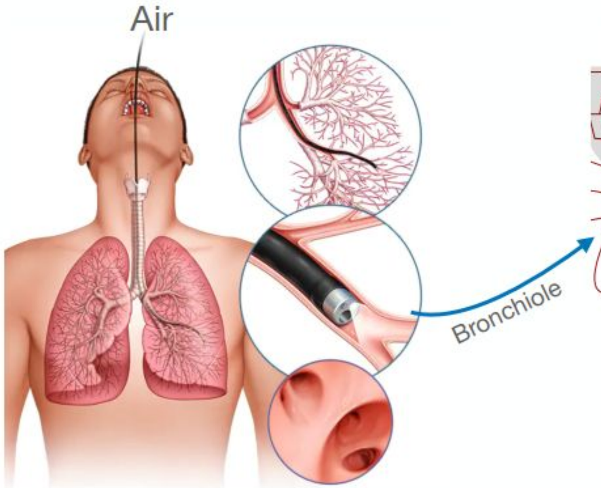

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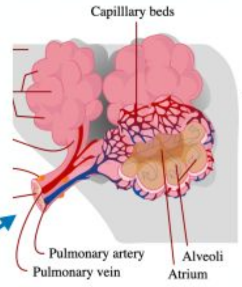

Courtesy: Wikipedia

Breathing in

Air → Mouth, Nose → Larynx, Trachea → Bronchi tubes → Bronchioles (smaller branches) → Alveoli (air sacs)

Air ← Mouth, Nose ← Larynx, Trachea ← Bronchi tubes ← Bronchioles (smaller branches) ← Alveoli (air sacs)

Breathing out

Infected Respiratory System

- **Fluid accumulation** in cavities (sinus) runny nose, cold
- **Obstruction** in the trachea sore throat
- **Inflammation** of bronchi pneumonia, asthma
- **Phlegm** in lungs COPD
- **Damaged** cells tuberculosis
- **Malignant** cells lung cancer

Courtesy: Mayo Foundation for Medical Education and Research

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Most common cause of global fatality
(2017 Report by Forum of Intl. Respiratory Societies)

#3: COPD

#4: Lower respiratory tract infection

#6: Tracheal, bronchial, and lung cancer

#12: Tuberculosis

#28: Asthma

!

Infected Respiratory System

Recommendations by 2017 Report by Forum of Intl. Respiratory Societies:

- Prevention cost is a fraction of treatment cost
- Early detection
- Design tools for early diagnosis and monitoring

Can we
do something which
helps solve the problem?

Infected Respiratory System

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Courtesy: Mayo Foundation for Medical Education and Research

Does it impact the acoustics?

Wind Instrument

- Blow air from one end
- Sound emanates from other end
- Practice makes you perfect

Result is music!

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- Blow air from one end
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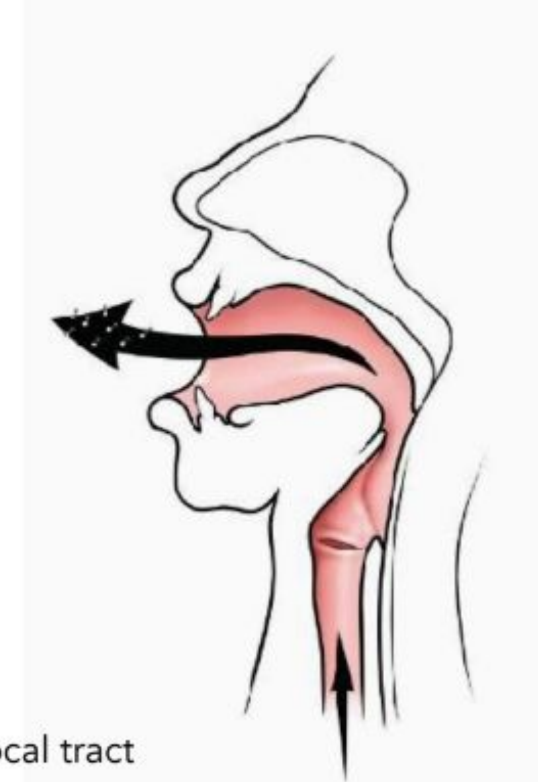
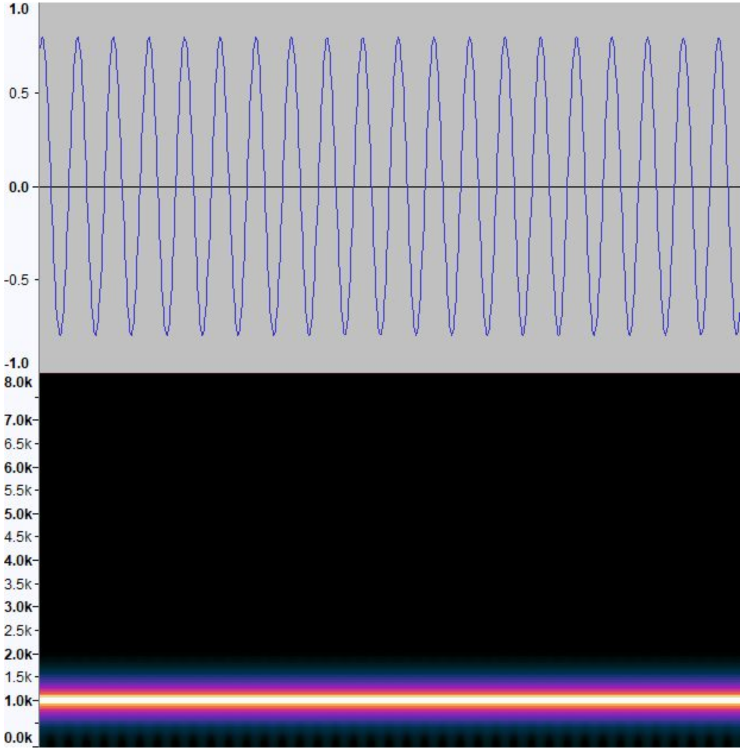


Vocal tract

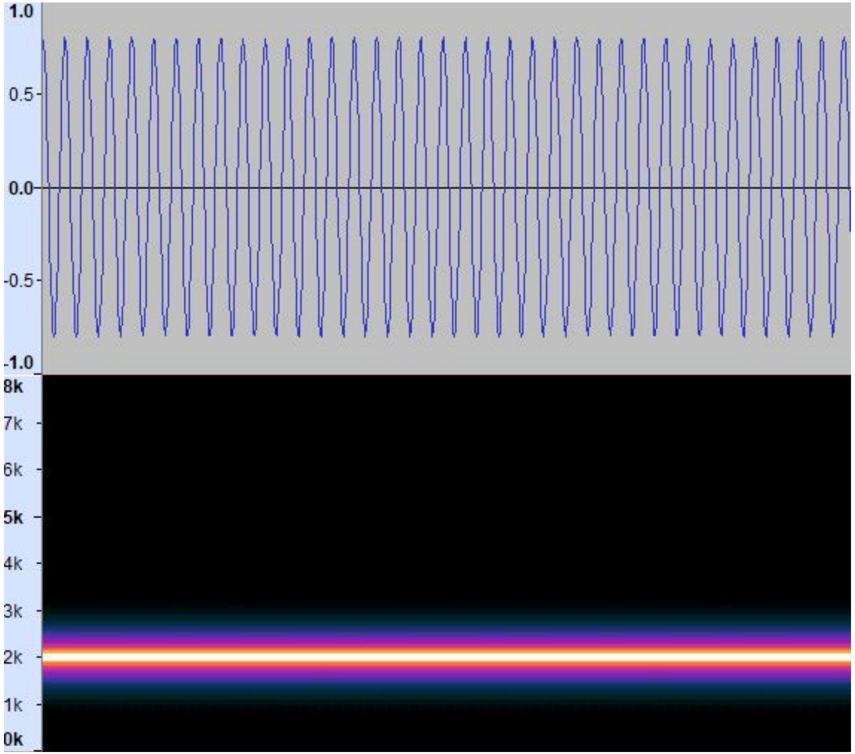
- Blow air from from one end …. lungs
- Sound emanates from other end …mouth
- An instrument playing inside you!

Result is your unique voice!

Tone signal at 1kHz



Tone signal at 1kHz



(Medical) Acoustic Perception

Courtesy: wikipedia

René Laennec

"A treatise on the diseases of the chest and on **mediate auscultation",** 1821

Mediate Auscultation or listening to internal body sounds

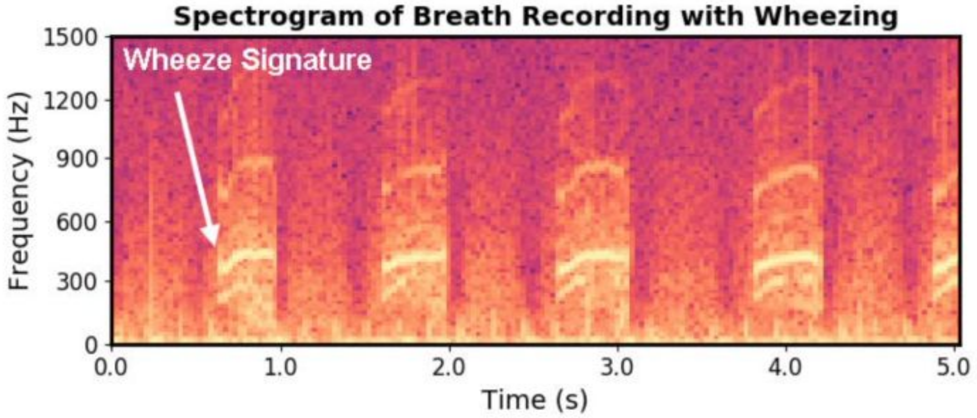
- Lungs
- Heart
- Intestines
- Arteries

(Medical) Acoustic Perception

Mediate Auscultation or listening to internal body sounds

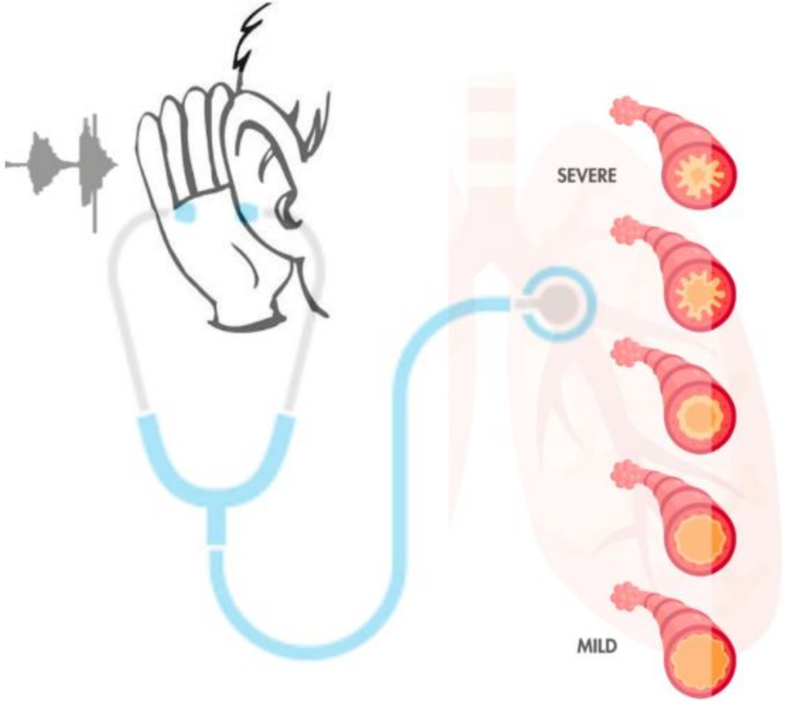
Lung sounds while **breathing**:

- wheezing



Courtesy: Shkel at al., Continuous Health Monitoring With Resonant-Microphone-Array-Based Wearable Stethoscope, IEEE Sensors, 2019

Listening using stethoscope

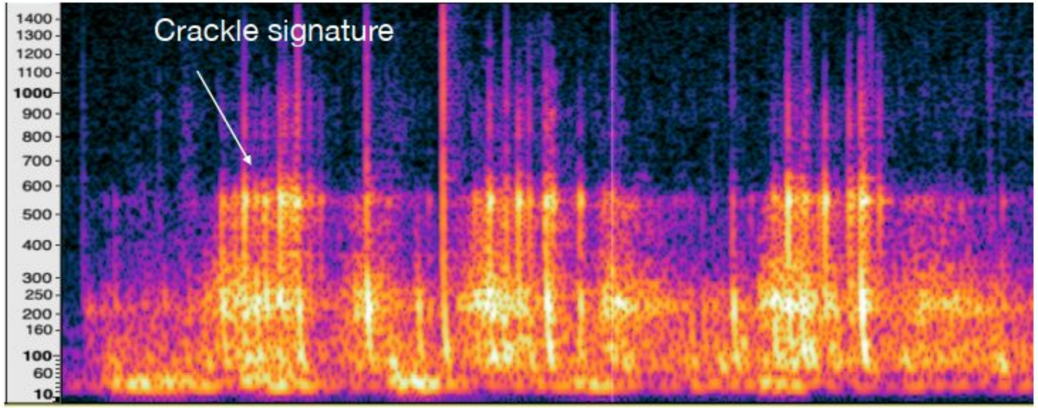


(Medical) Acoustic Perception

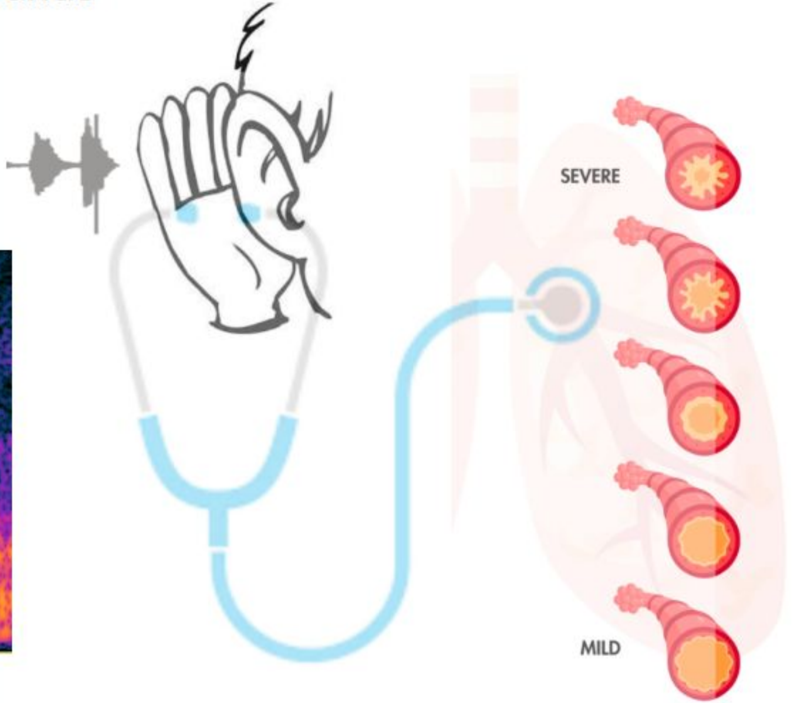
Mediate Auscultation or listening to internal body sounds

Lung sounds while **breathing**:

- wheezing
- Crackle



Listening using stethoscope

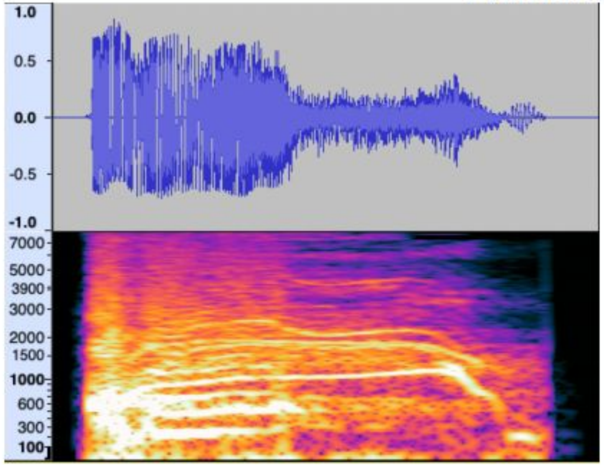


(Medical) Acoustic Perception

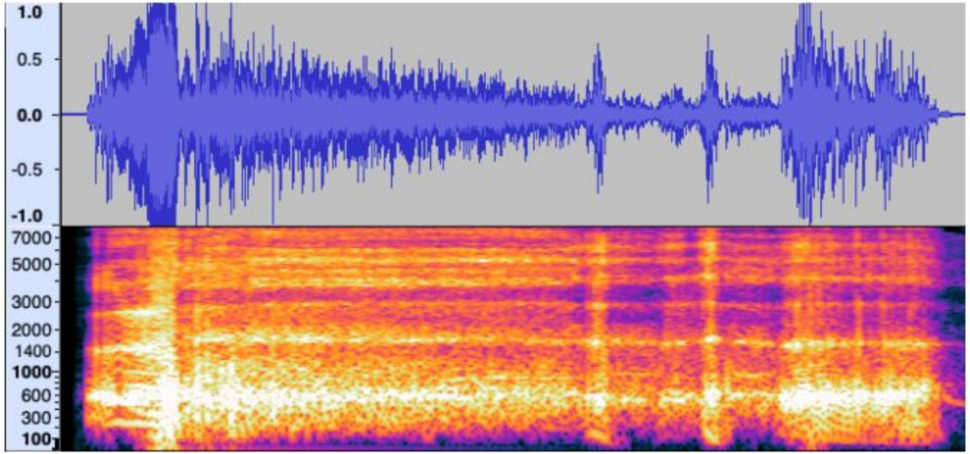
Mediate Auscultation or listening to internal body sounds

Lung sounds while **coughing**:

Asthma



COPD



Audio Courtesy: Smith et al., The description of cough sounds by healthcare professionals, Cough, 2006.

Infected Respiratory System

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Courtesy: Mayo Foundation for Medical Education and Research

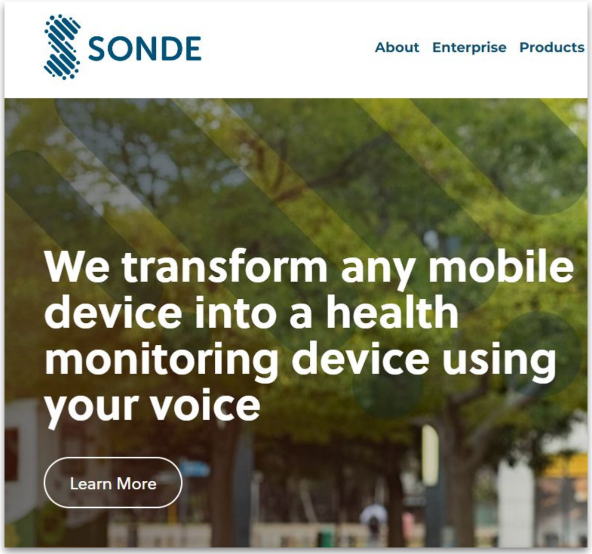
Does it impact the acoustics? To an extent, yes!

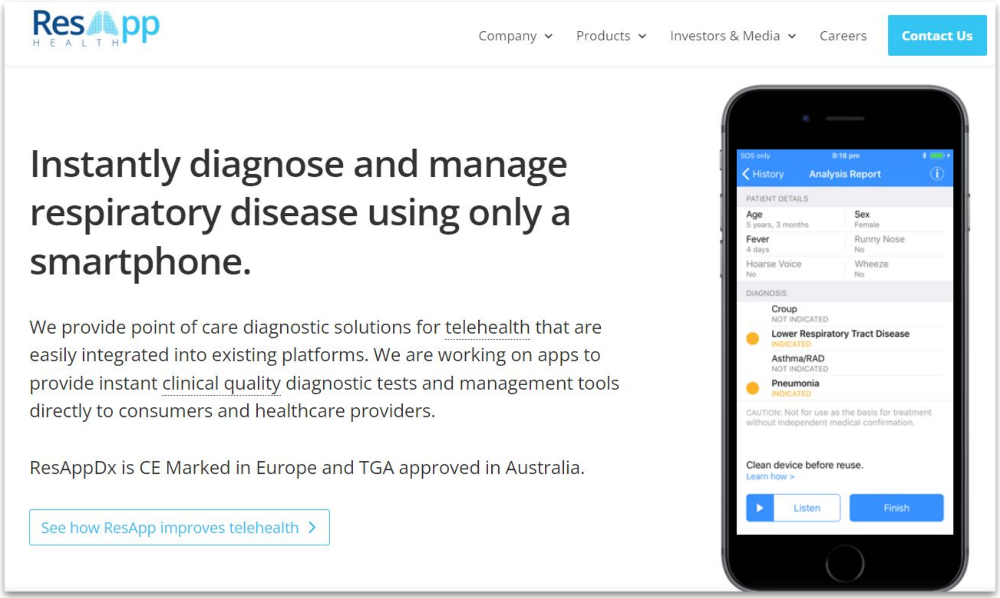
Infected Respiratory System

Can automatic analysis of respiratory sound recordings help in screening/ diagnosis?

- Gained interest (Gurung et al., Computerised lung sound analysis for automatic detection of abnormal lung sounds, Respiratory Medicine, 2011)
- Pertusis (whooping cough) detection (Pramono et al., PLoS, 2016)
- Tuberculosis detection (Botha et al., Physiological Measurement, 2018)
- Pneumonia (Abeyratne et al., Annals Biomedical Engg., 2013)
- Asthma, COPD (Hee et al., Applied Sciences, 2019)
- Dataset (Rocha et al., An open access database for the evaluation of respiratory sound classification algorithms, Physiological Measurements, 2019)

Science to technology ….





Overview

Four parts

1 Respiratory Acoustics: Motivation

2 **Linking to something current: COVID-19**

3 Dataset Creation

4 Dataset Analysis

COVID-19

On 12th Dec, from

64,631

new cases in last 24hrs

649,038,437

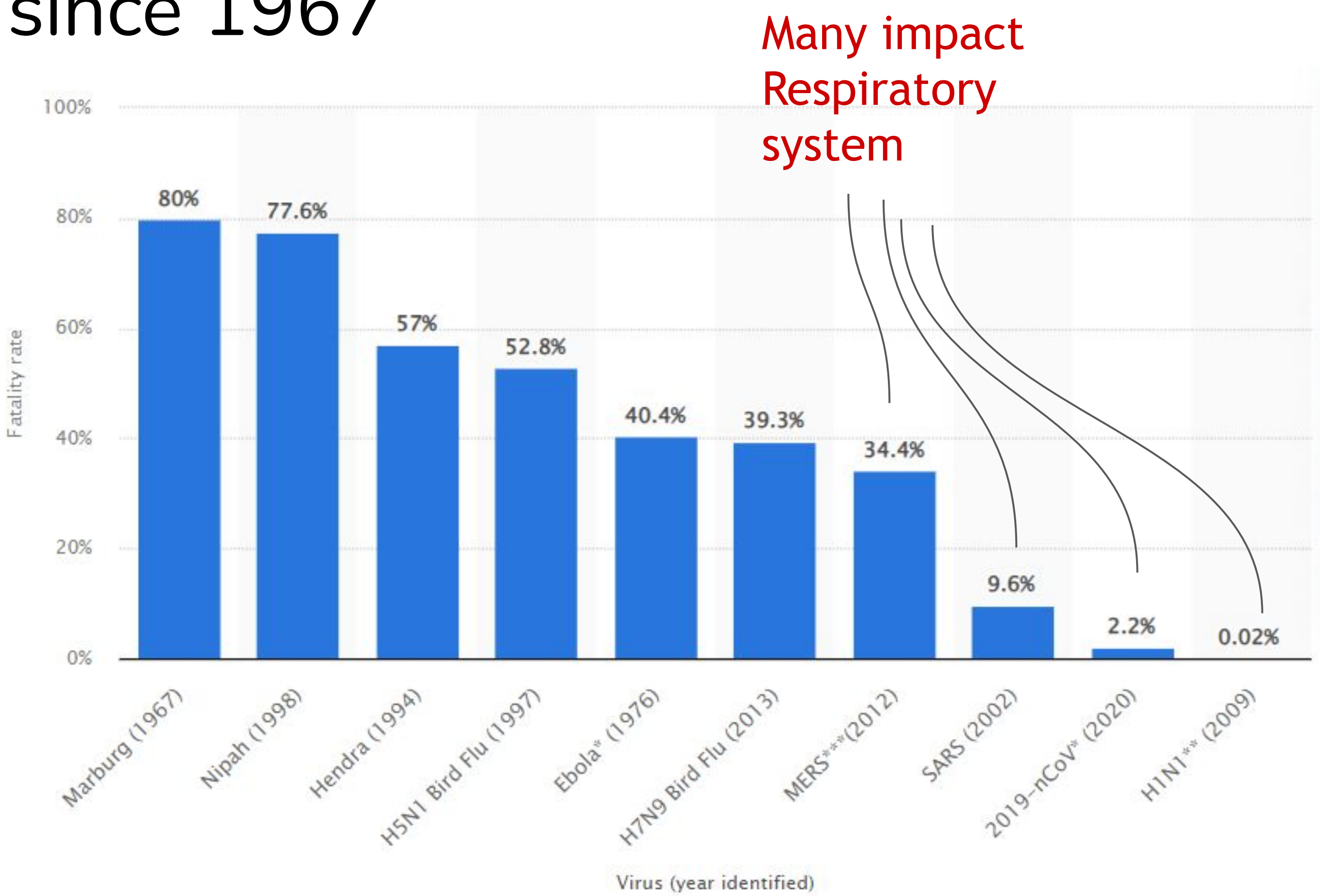
cumulative cases

6,645,812

cumulative deaths

Outbreaks since 1967

(as of Jan 2020)



COVID-19 Disease

Symptoms

- Respiratory infection
  - Traverses from upper to lower respiratory tract (Hu et al., Nature Reviews Microbiology, 2020)
- Study on 281, 641 COVID-19 infected individuals (Li et al., Medical Virology, 2021)
  - Fever (79%), Cough (54%), and malaise (38%)
- Shortness of breathe, decreased blood oxygen content

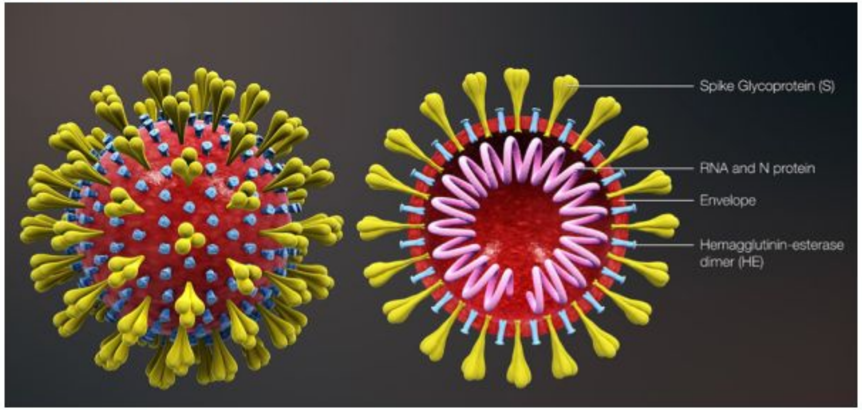
COVID-19 Disease

Current testing strategies

- Molecular testing
  - RT-PCR
  - Rapid Antigen Test (RAT/Snell)

- Screening (and prognosis)
  - Chest CT scan
  - Chest X-ray

- SARS-CoV-2 Virus

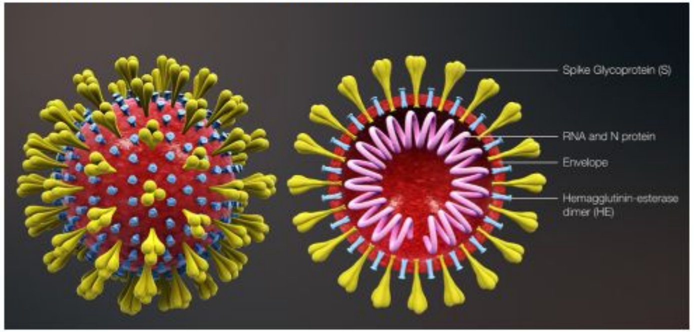


COVID-19 Disease

Current testing limitations

- Needs expertise (human, and chemical)
- Time taking, and costly
- Physical distancing
- Not scalable

- SARS-CoV-2 Virus



WHO recommends: Design of point-of-care technology-driven tests for screening and diagnosis

Overview

Four parts

1

Respiratory Acoustics: Motivation

2

Linking to something current: COVID-19

3

Dataset Creation

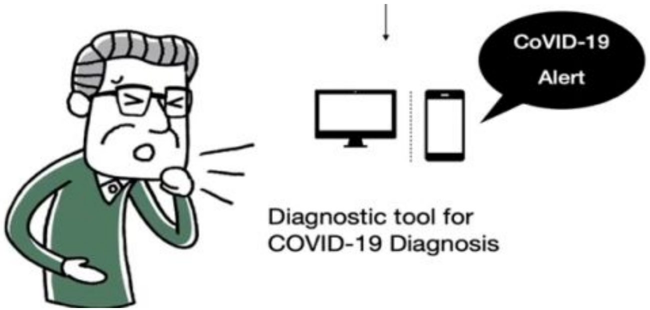
4

Dataset Analysis

Project Coswara

Launched on: 14th April, 2020

Co (covid) + *swara* (sound)



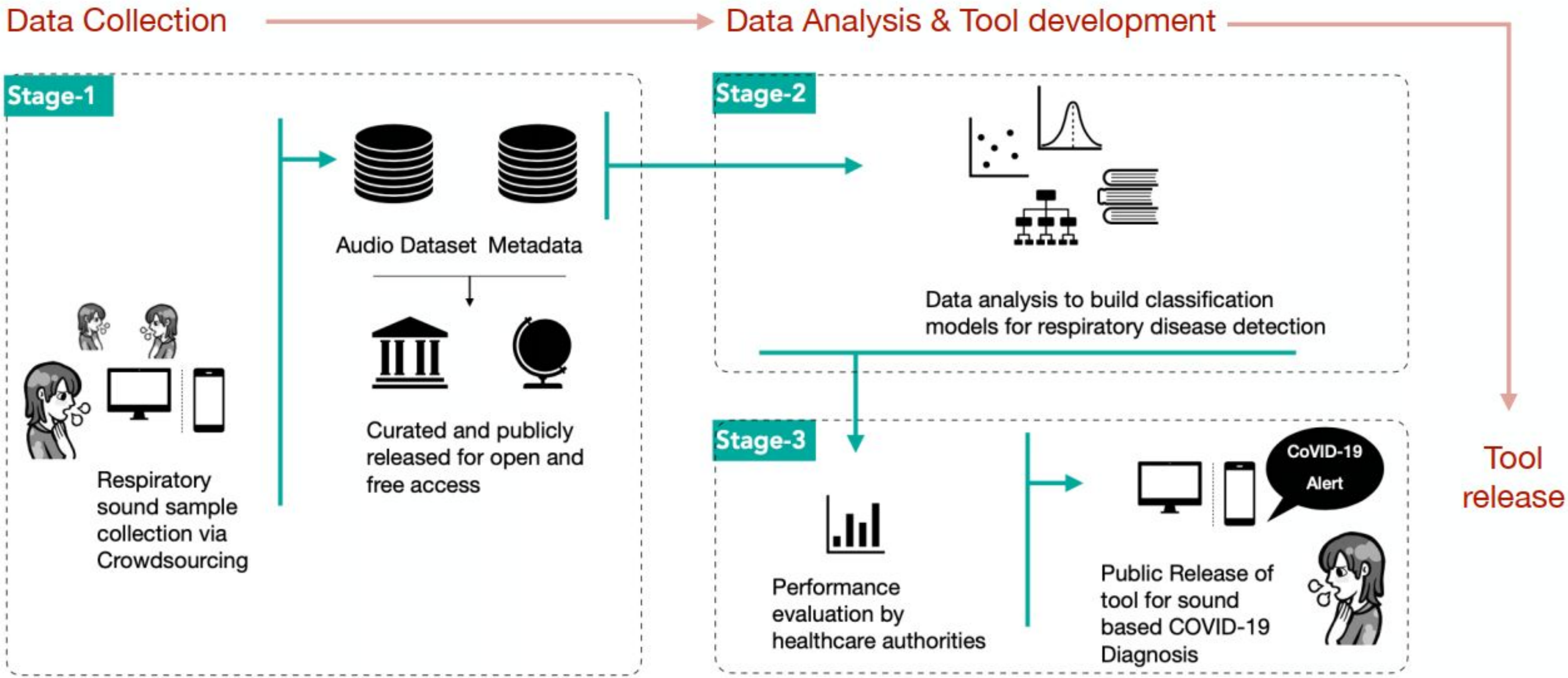
Project Coswara

Launched on: 14th April, 2020

Co (covid) + *swara* (sound)

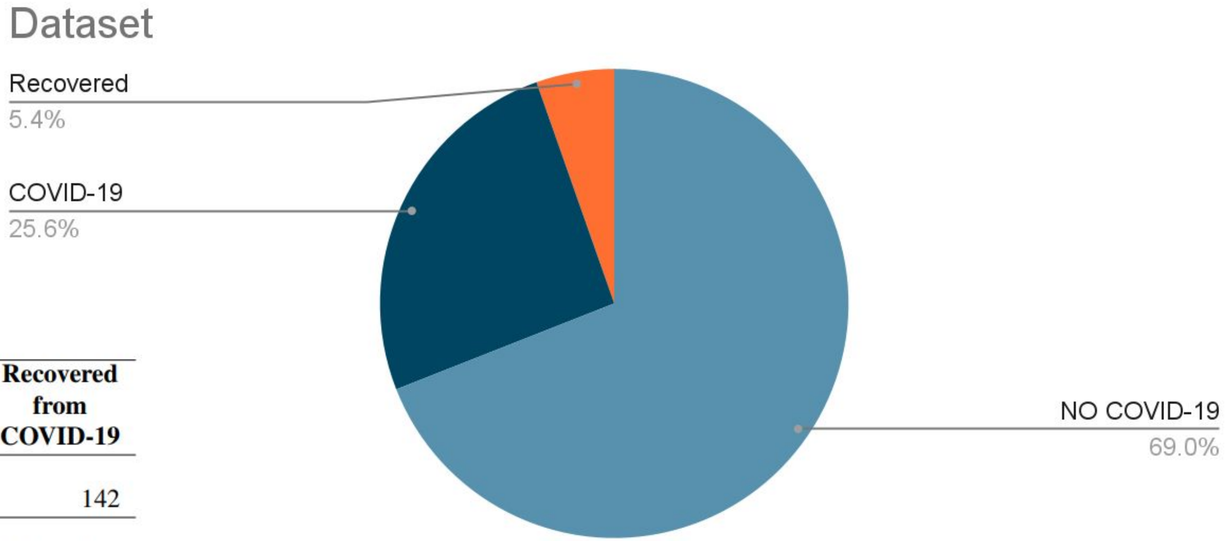
- Data collection (Stage 1)
- Data analysis (Stage 2)
- Screening tool development and release (Stage 3)

Project Coswara

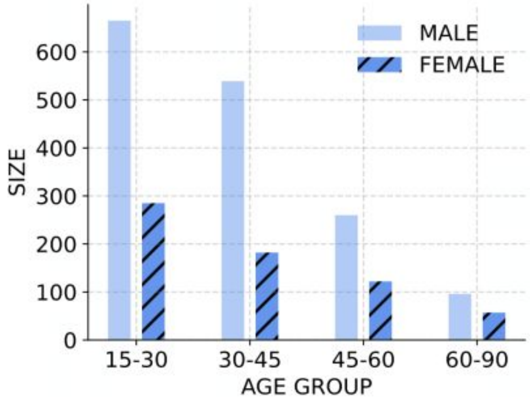


Coswara

Metadata



Coswara Dataset	No COVID-19	COVID-19	Recovered from COVID-19
Subject			
Count	1819	674	142
Sex			
Male	1334 (73.3%)	409 (60.7%)	76 (53.5%)
Female	485 (26.7%)	264 (39.3%)	66 (46.5%)
Age			
15-30	934 (51.3%)	264 (39.2%)	64 (45.1%)
30-45	554 (30.5%)	175 (26%)	40 (28.2%)
45-60	261 (14.3%)	153 (22.7%)	28 (19.7%)
60-90	70 (3.9%)	82 (12.1%)	10 (7%)
Indian Province			
Karnataka	654 (36%)	322 (47.8%)	70 (49.3%)
Tamil Nadu	206 (11.3%)	247 (36.6%)	42 (29.6%)
Maharashtra	182 (10%)	42 (6.2%)	11 (7.7%)
Kerala	63 (3.5%)	17 (2.5%)	2 (1.4%)
Others	507 (27.9%)	34 (5%)	12 (8.5%)



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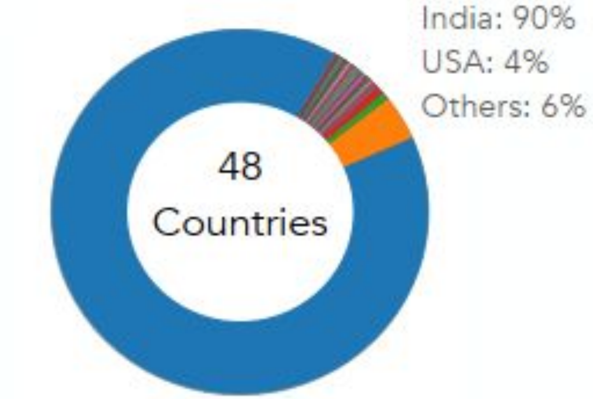
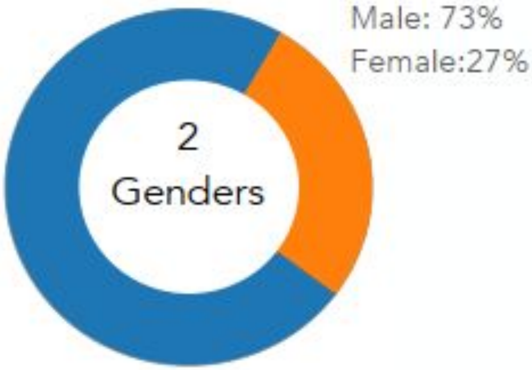
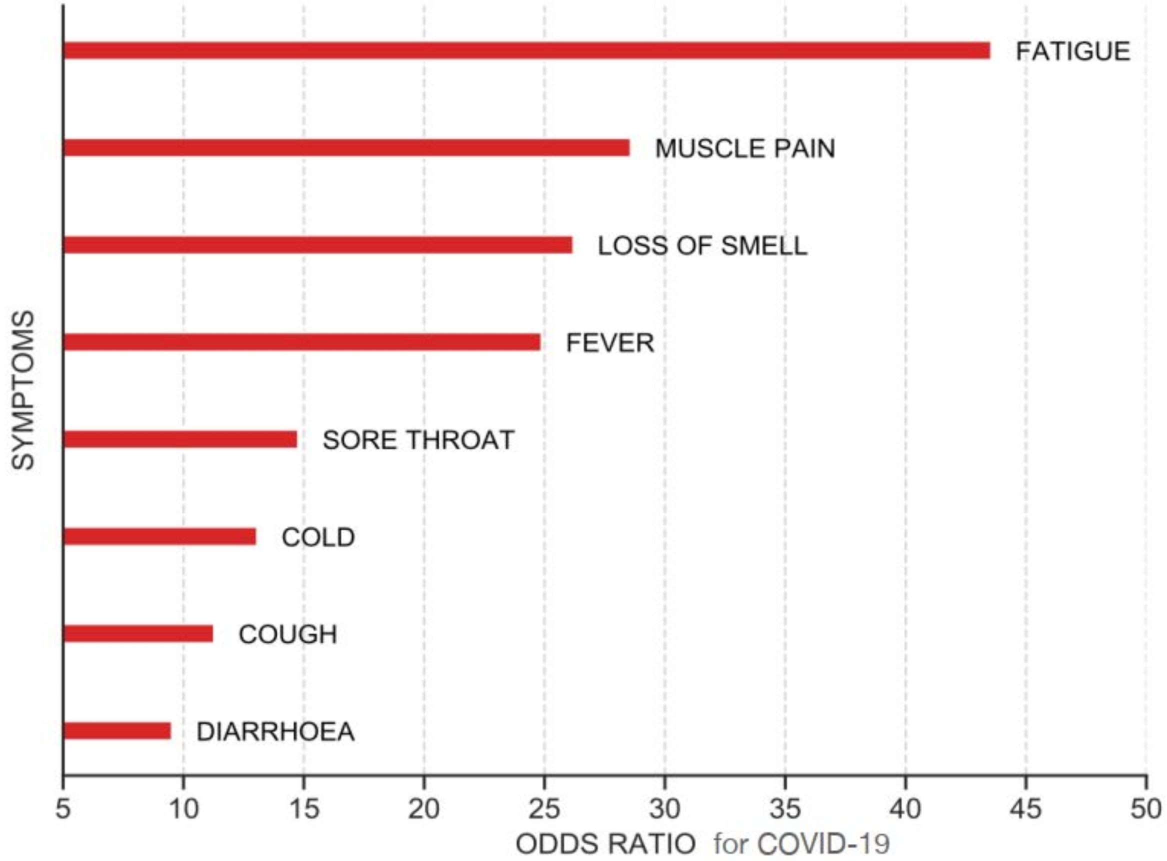




Coswara

Symptom data



Coswara

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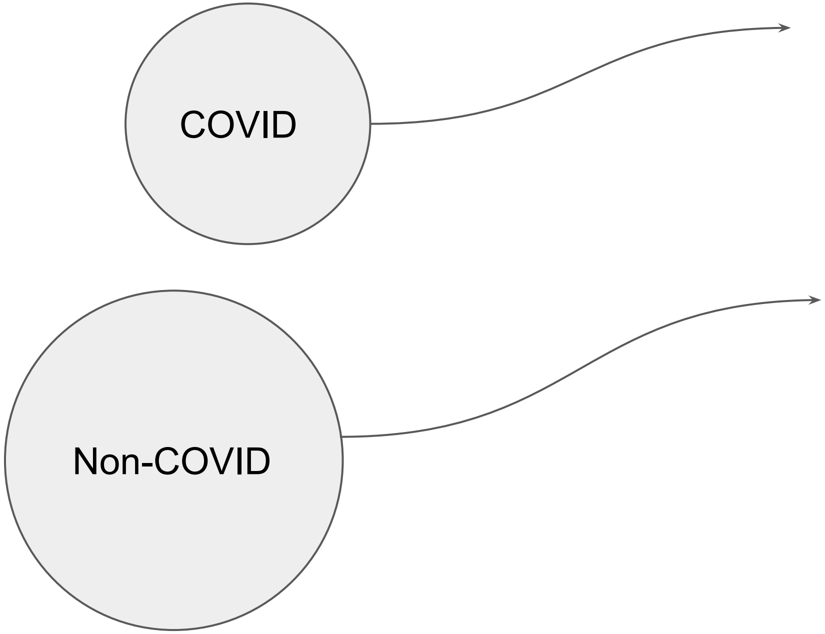


Subject Category	Subject sub-category	Health status description
COVID	Asymp	COVID-19 positive status with no symptoms
	Mild	COVID-19 positive status with mild symptoms
	Moderate	COVID-19 positive status with moderate symptoms
Non-COVID	Healthy	COVID-19 negative status with no respiratory-ailments, and without COVID-like symptoms
	Resp. ail	COVID-19 negative status with pre-existing respiratory ailments including asthma, pneumonia, or chronic lung disease
	Symp	COVID-19 negative status with no respiratory ailments but has one or more COVID-19-like symptoms such as cough, cold, fever, loss of smell or muscle fatigue

Coswara

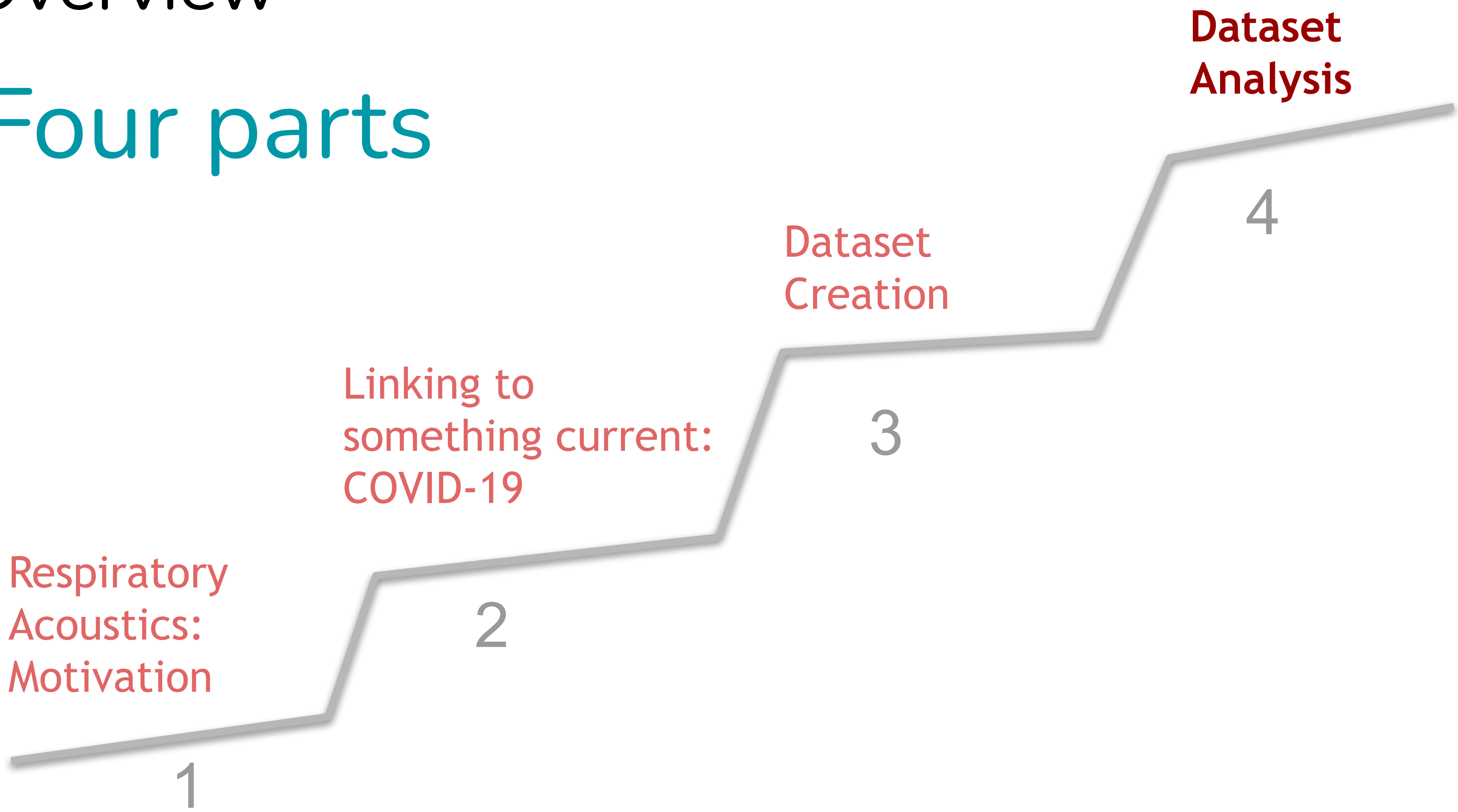
Audio data

User

1. Breathing-shallow (B-S)
2. Breathing-deep (B-D)
3. Cough-shallow (C-S)
4. Cough-heavy (C-H)
5. Vowel-o (V-O)
6. Vowel-e (V-E)
7. Vowel-a (V-A)
8. Counting-normal (C-N)
9. Counting-fast (C-F)

Overview

Four parts



Coswara

~51 hours

Audio data

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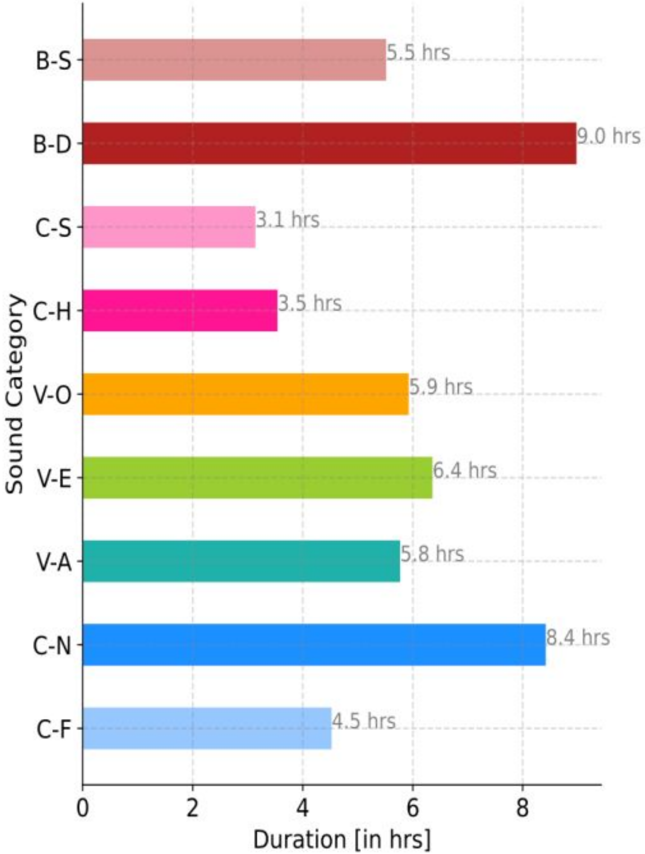
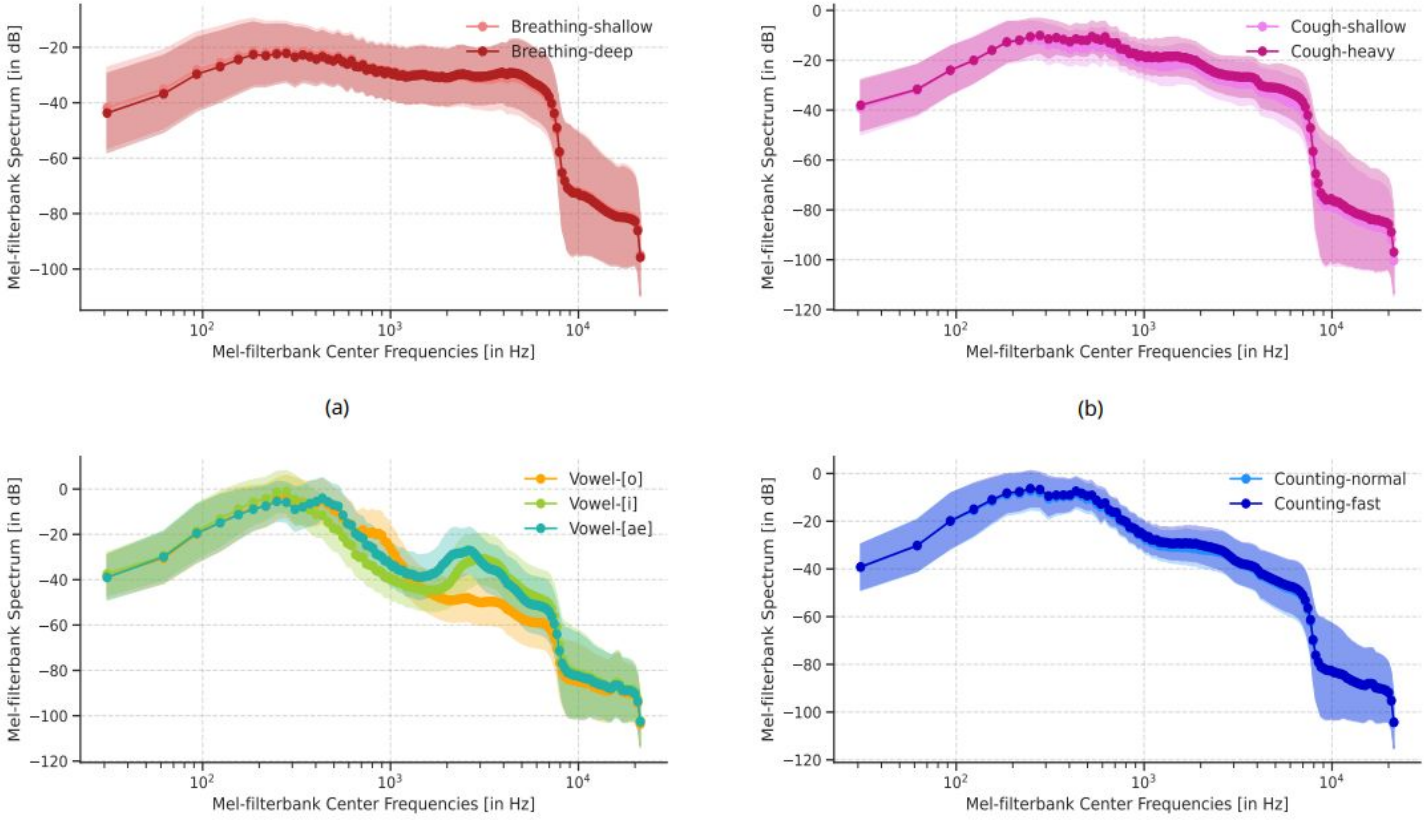
8. Counting-normal (C-N)
9. Counting-fast (C-F)



Coswara

Audio data

Sound category comparison: Mel-spectrogram features

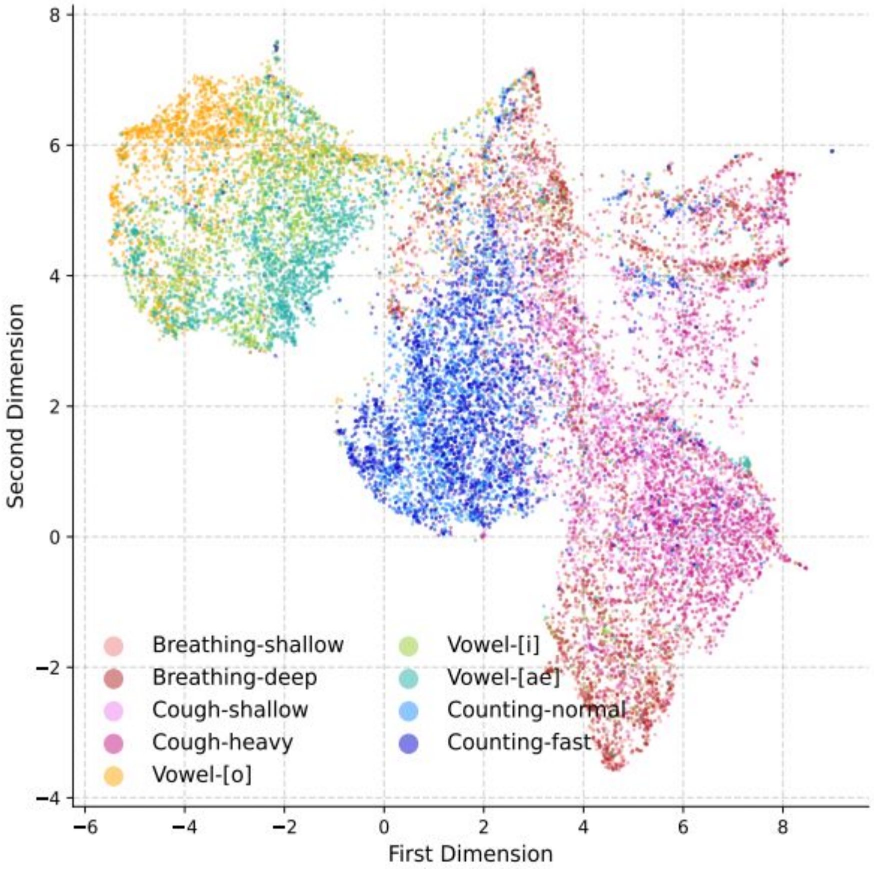


Coswara

Audio data

9 sound categories:
help characterize the respiratory system

Spectral feature projection using UMAP

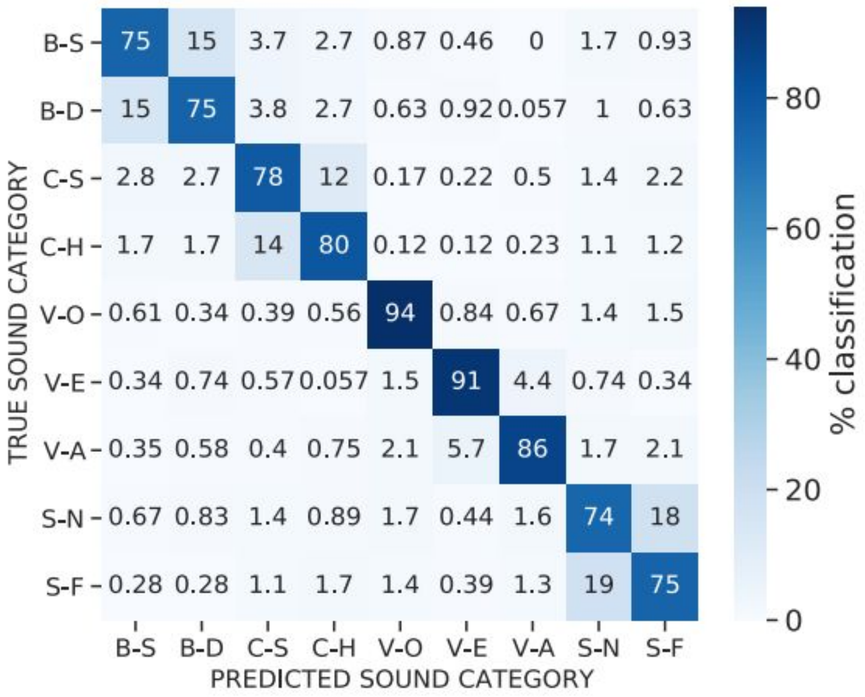


Coswara

Audio data

Easily classified into 9 categories

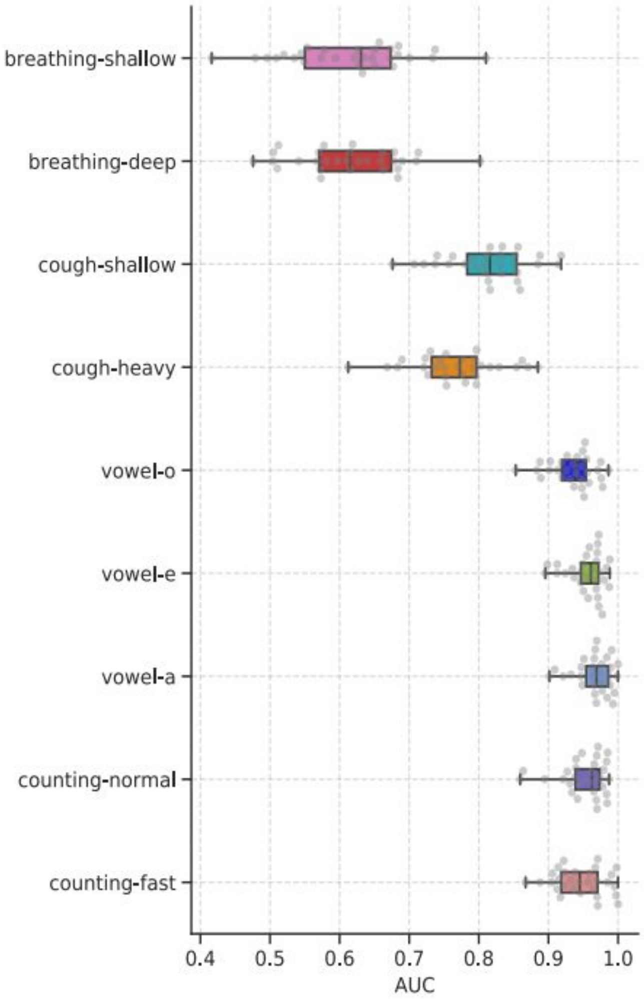
Confusion matrix: Random forest classifier



Coswara

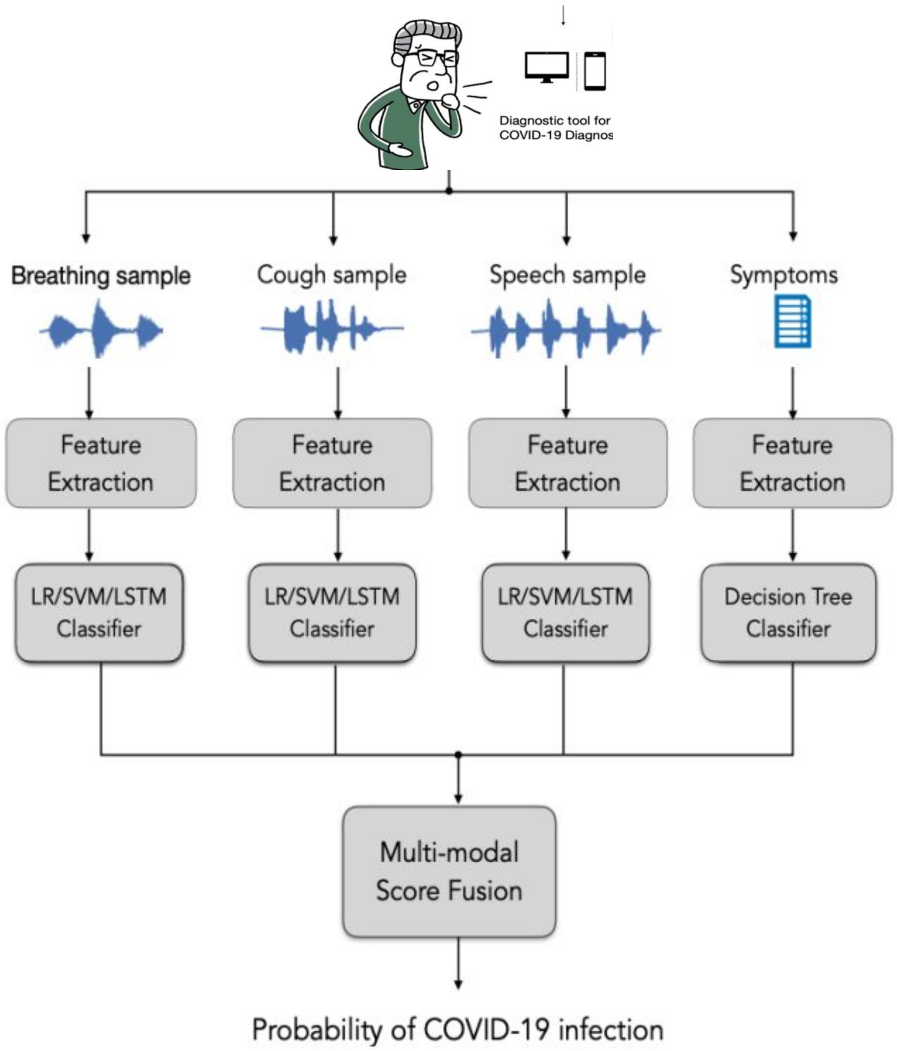
Audio data

Easily classified into two genders - male/female



Coswara

COVID classification



Coswara COVID classification

Sample name	Sample description
Breathing	breathing-shallow breathing-deep
Cough	cough-shallow cough-heavy
Vowel phonation	vowel-[u] vowel-[i] vowel-[ae]
Speech	Counting normal Counting fast

Two-class classification

- Class imbalance
- Area Under ROC curve
  - Chance = 50%
  - Higher the better

Coswara COVID classification

Sample name	Sample description	Classifier performance on test set (AUC %)				
		LR	RF	MLP	BLSTM	Transformer
Breathing	breathing-shallow	69.9(64.9-74.5)	76.6(71.7-80.9)	78.6(74.2-82.8)	77.9(73.5-81.9)	78.1(73.8-82.1)
	breathing-deep	68.7(63.6-73.7)	74.0(68.5-78.5)	74.5(69.4-78.8)	75.7(71.0-80.2)	76.7(71.9-81.2)
Cough	cough-shallow	73.6(68.6-77.9)	77.1(72.4-81.2)	76.8(72.0-81.1)	76.6(71.7-80.8)	75.5(70.8-79.7)
	cough-heavy	74.3(69.5-78.5)	79.3(74.9-83.2)	78.6(74.3-82.5)	79.8(75.3-83.9)	79.4(75.1-83.3)
Vowel phonation	vowel-[u]	70.0(65.1-74.5)	75.7(71.3-80.0)	73.2(68.5-77.5)	73.6(68.4-78.6)	74.9(69.9-79.6)
	vowel-[i]	69.4(64.5-74.1)	74.3(69.2-79.0)	69.6(64.0-74.3)	77.3(73.1-81.9)	77.5(73.3-81.9)
	vowel-[ae]	71.1(66.4-75.6)	77.3(72.9-81.4)	70.5(65.4-75.0)	79.3(74.5-83.4)	78.6(74.0-82.6)
Speech	Counting normal	69.4(64.5-73.9)	76.0(71.1-80.2)	75.7(71.1-80.0)	80.8(76.6-84.7)	80.1(75.7-83.8)
	Counting fast	71.7(67.3-76.2)	75.7(71.4-79.9)	73.7(68.5-78.3)	79.4(74.5-83.6)	79.3(74.5-83.6)

Coswara COVID classification

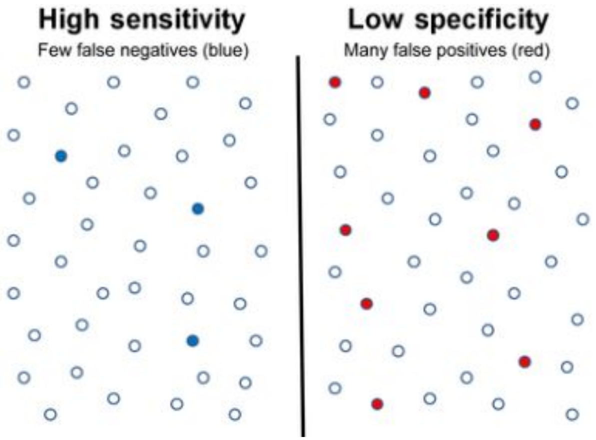
Sample name	Sample description	Classifier performance on test set (AUC %)				
		LR	RF	MLP	BLSTM	Transformer
Breathing	breathing-shallow	69.9(64.9-74.5)	76.6(71.7-80.9)	78.6(74.2-82.8)	77.9(73.5-81.9)	78.1(73.8-82.1)
	breathing-deep	68.7(63.6-73.7)	74.0(68.5-78.5)	74.5(69.4-78.8)	75.7(71.0-80.2)	76.7(71.9-81.2)
Cough	cough-shallow	73.6(68.6-77.9)	77.1(72.4-81.2)	76.8(72.0-81.1)	76.6(71.7-80.8)	75.5(70.8-79.7)
	cough-heavy	74.3(69.5-78.5)	79.3(74.9-83.2)	78.6(74.3-82.5)	79.8(75.3-83.9)	79.4(75.1-83.3)
Vowel phonation	vowel-[u]	70.0(65.1-74.5)	75.7(71.3-80.0)	73.2(68.5-77.5)	73.6(68.4-78.6)	74.9(69.9-79.6)
	vowel-[i]	69.4(64.5-74.1)	74.3(69.2-79.0)	69.6(64.0-74.3)	77.3(73.1-81.9)	77.5(73.3-81.9)
	vowel-[ae]	71.1(66.4-75.6)	77.3(72.9-81.4)	70.5(65.4-75.0)	79.3(74.5-83.4)	78.6(74.0-82.6)
Speech	Counting normal	69.4(64.5-73.9)	76.0(71.1-80.2)	75.7(71.1-80.0)	80.8(76.6-84.7)	80.1(75.7-83.8)
	Counting fast	71.7(67.3-76.2)	75.7(71.4-79.9)	73.7(68.5-78.3)	79.4(74.5-83.6)	79.3(74.5-83.6)
Sound fusion	Joint inference using all sound categories	73.9(69.1-78.2)	78.9(74.4-82.6)	76.2(71.4-80.6)	84.1(80.1-87.8)	84.1(80.2-87.7)

Coswara COVID classification

Sample name	Sample description	Classifier performance on test set (AUC %)				
		LR	RF	MLP	BLSTM	Transformer
Breathing	breathing-shallow	69.9(64.9-74.5)	76.6(71.7-80.9)	78.6(74.2-82.8)	77.9(73.5-81.9)	78.1(73.8-82.1)
	breathing-deep	68.7(63.6-73.7)	74.0(68.5-78.5)	74.5(69.4-78.8)	75.7(71.0-80.2)	76.7(71.9-81.2)
Cough	cough-shallow	73.6(68.6-77.9)	77.1(72.4-81.2)	76.8(72.0-81.1)	76.6(71.7-80.8)	75.5(70.8-79.7)
	cough-heavy	74.3(69.5-78.5)	79.3(74.9-83.2)	78.6(74.3-82.5)	79.8(75.3-83.9)	79.4(75.1-83.3)
Vowel phonation	vowel-[u]	70.0(65.1-74.5)	75.7(71.3-80.0)	73.2(68.5-77.5)	73.6(68.4-78.6)	74.9(69.9-79.6)
	vowel-[i]	69.4(64.5-74.1)	74.3(69.2-79.0)	69.6(64.0-74.3)	77.3(73.1-81.9)	77.5(73.3-81.9)
	vowel-[ae]	71.1(66.4-75.6)	77.3(72.9-81.4)	70.5(65.4-75.0)	79.3(74.5-83.4)	78.6(74.0-82.6)
Speech	Counting normal	69.4(64.5-73.9)	76.0(71.1-80.2)	75.7(71.1-80.0)	80.8(76.6-84.7)	80.1(75.7-83.8)
	Counting fast	71.7(67.3-76.2)	75.7(71.4-79.9)	73.7(68.5-78.3)	79.4(74.5-83.6)	79.3(74.5-83.6)
Sound fusion	Joint inference using all sound categories	73.9(69.1-78.2)	78.9(74.4-82.6)	76.2(71.4-80.6)	84.1(80.1-87.8)	84.1(80.2-87.7)
Sound plus symptom fusion	Joint inference using all sound categories plus symptom	89.2(85.8-92.1)	91.2(88.2-93.8)	90.1(86.9-93.0)	92.1(89.3-94.4)	92.0(89.2-94.1)

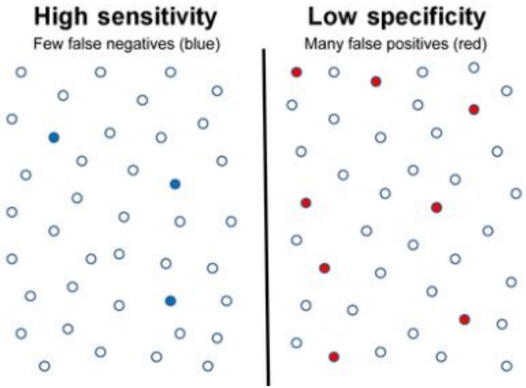
Coswara

COVID classification

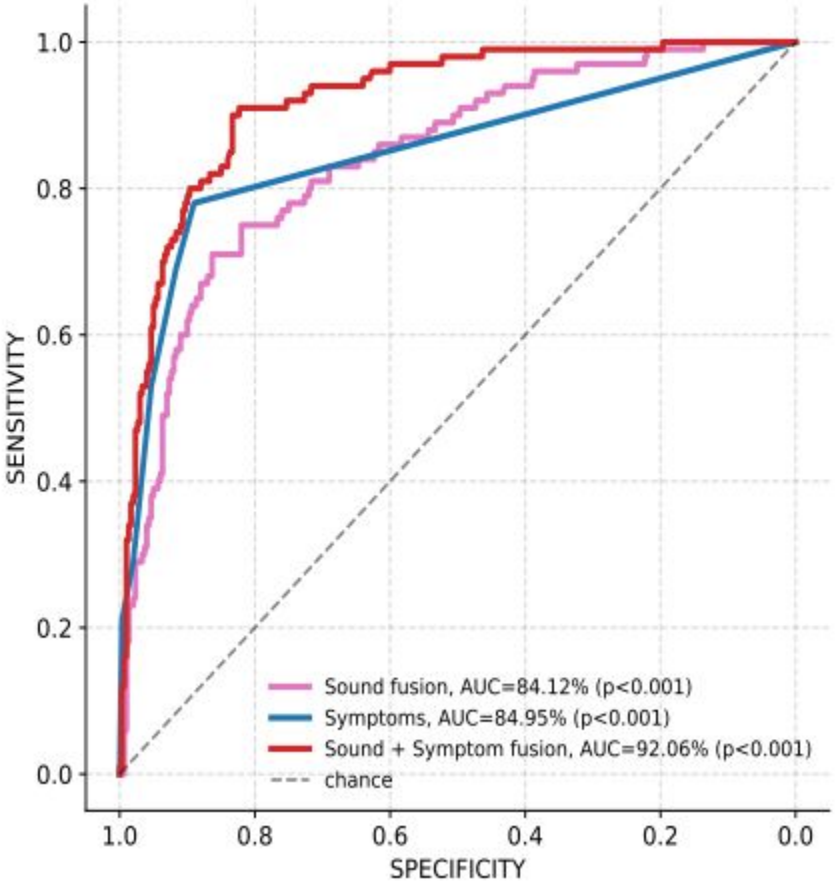


Coswara

COVID classification

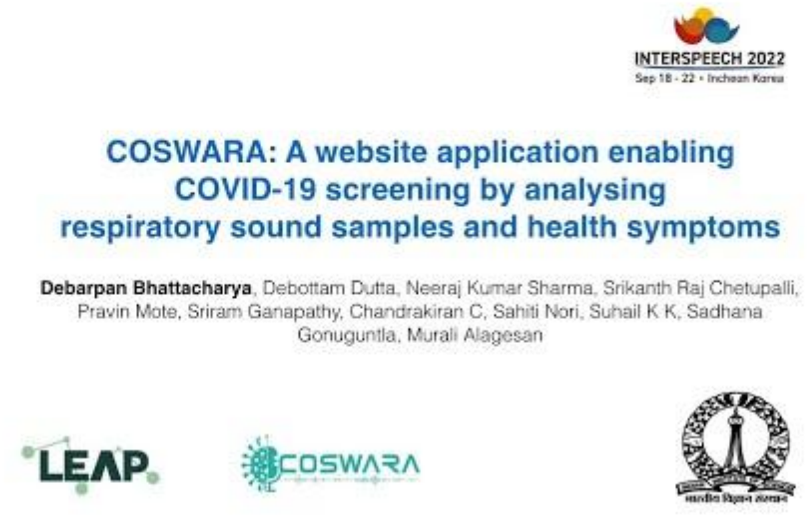


- COVID detection works!
- Sound fusion helps
- Symptoms helps



Coswara

COVID Screening tool



Coswara Dataset Release

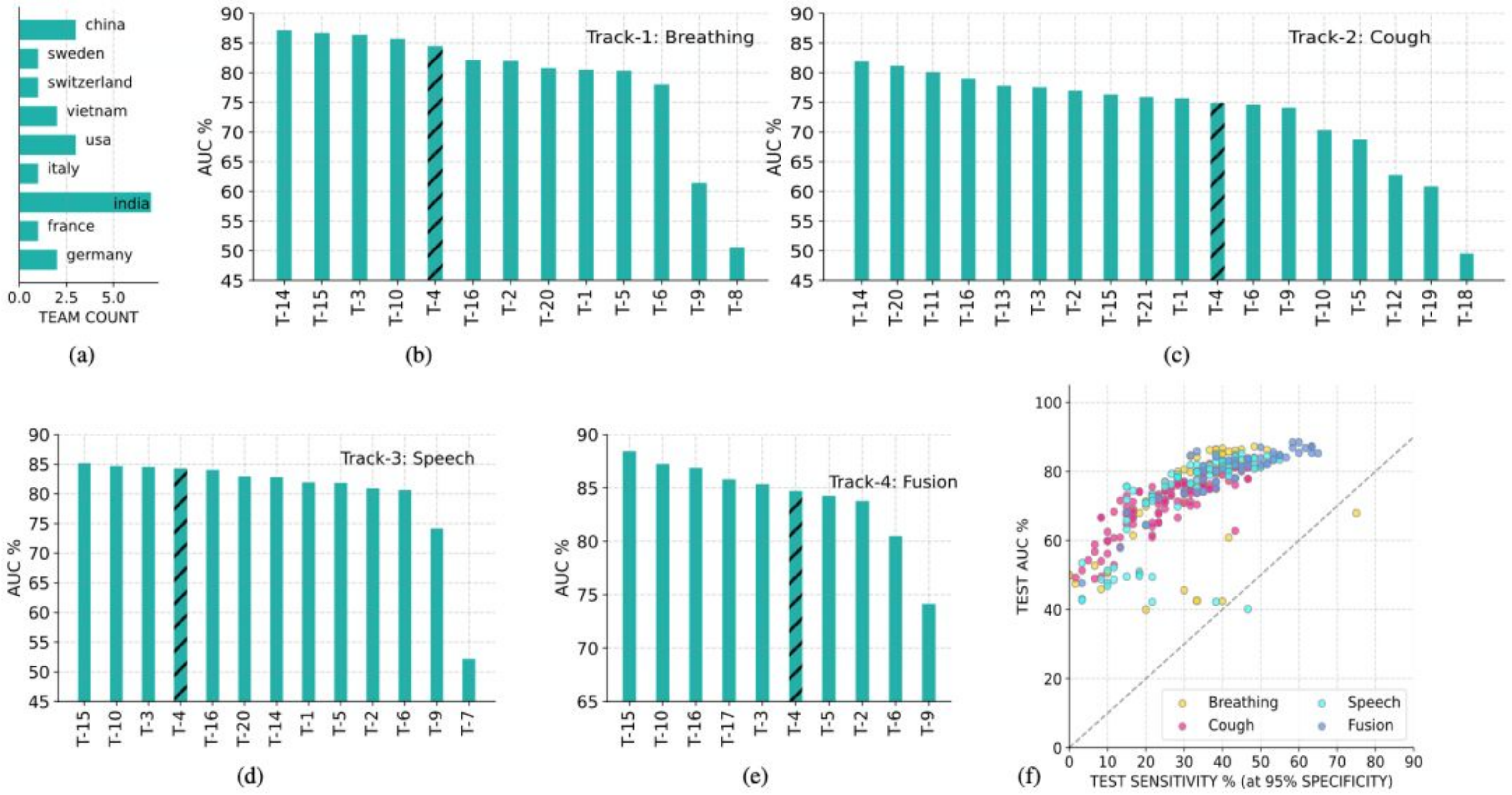
Dataset Name	Sound data	Sound samples per subject	Access	Sound file format	Sound quality curation	COVID-19 screening tool deployed	Meta-data	Primary Data collection site	Subject count		
									No COVID-19	COVID-19	Recovered from COVID-19
COUGHVID [21]	Cough	1	Open	WEBM	None	No	Gender Age Other diseases Symptoms Location	Europe	26395	1155	None
COVID-19 Sounds [22]	Cough Breathing Speech	3	Request	MP3	None	No	Gender Medical history Symptoms Hospitalization	UK	6450	2106	None
Tos COVID-19 [23]	Cough	1	Open	OGG	None	No	Gender Age Symptoms Location	Argentina	125183	21197	None
Coswara (This paper)	Cough Breathing Vowel phonation Speech	9	Open	WAV	Human listening	Yes	Gender Age Country Symptoms Other ailments Vaccination and more	India	1819	674	142

Coswara Dataset Challenge

- ISCA Interspeech
  - Feb-Mar, 2021
- IEEE ICASSP
  - Aug-Sept, 2021

Diagnosis of COVID-19 using Acoustics Challenge

Coswara Dataset Challenge



Summary

- Respiratory Infection impacts acoustics
- Detection using acoustics can be impactful
- COVID-19 detection performance better than chance, AUC > 80%
- Other groups also getting similar performance
- Scaling efforts

Coswara: A team work

Researchers

- [Project Associates] Anand Mohan, Ananya Muguli, Prashant Krishnan, Rohit Kumar, Shreyas Ramoji, Pravin Mote, Debottam Dutta
- [Masters] Debarpan Bhattacharya
- [Post Docs] Neeraj Sharma (myself), Srikanth Raj Chetupalli
- [Professors] Sriram Ganapathy (Principal Investigator), Prasanta Kumar Ghosh
- And volunteers who helped as listeners

Medical Doctors

- Lancelot Pinto, Chandra Kiran, Mohammed Suhail, Sahiti Nori, Sadhana Gonuguntla, Shrirama Bhat, Nirmala R

“Citizens” of Science

- Voluntary participants who recorded their data

Acknowledgment

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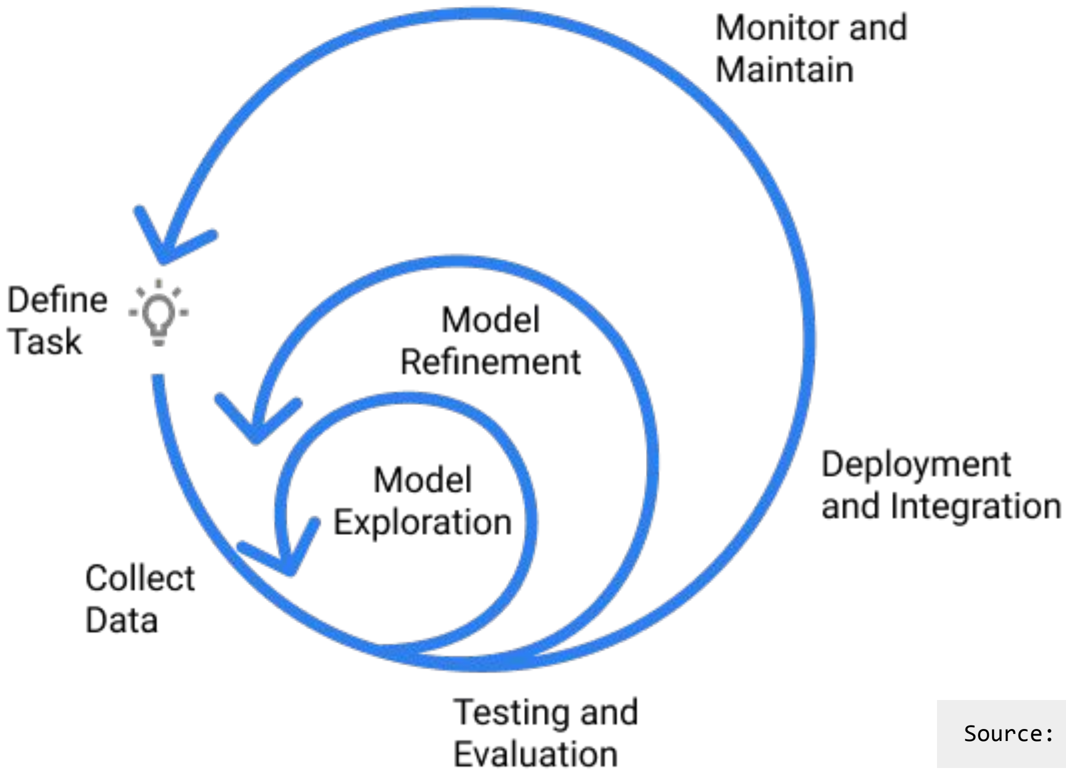
- CV Raman Postdoctoral Fellowship (Neeraj Sharma)
- Department Science and Technology RASHAK program

Support

- Indian Institute of Science, Bangalore

Machine Learning Project Development Cycle



Source: https://www.jeremyjordan.me/

Know more about projects pursued by DA623 in Winter 23

https://neerajww.github.io/da623BookV23/intro.html

- Welcome to DA623 Projects
- Ideation: Topics, utilities, and datasets
- Project Plan Meet
- Voice Analytics
- Singing voice separation
- Rotating shaft analysis
- COPD Detection
- Speaker Diarization
- Piano Music
- Gravitational Wave
- Epileptic Seizures
- Bird Sound Recognition
- Emotion Recognition
- Signal Denoising
- Accent Transfer
- Sound Visualisation
- Beat Synchronization
- Parkinson Diagnosis