

Health AI in Nepal: Excellence in Resource Constraints

Bishesh Khanal, PhD

bishesh.khanal@naamii.org.np

**Founding Chairperson & Research Scientist,
NAAMII, Nepal**

<https://naamii.org>

Advisor/Adjunct Faculty

Centre for Digital Technologies in Healthcare (CDiTH) / IIIT Hyderabad, India

12th National Summit of Health and Population Scientists in Nepal

National Health Research Council, Nepal

Kathmandu, Nepal

10 April 2026



Other Engagements

Visiting Lectures at Msc Public Health in University of Cambridge, UK

PhD Supervisions: Rochester Institute of Technology, USA; Duke University, USA; University of Barcelona, Spain; University of Tübingen, German.

Disclaimers, Conflict of Interests

- ***Terahs Technology (Co-founder; equity holding)***
- Tangible.careers (Co-founder; equity holding)
- Diyo.ai (Co-founder; equity holding)

Co-founders of NAAMII



BE, Electronics Engineering



PhD, Computational Medicine



NAAMII



Msc: 1. Computer Vision (Robotics)
2. Computational Biology & Biomedicine



Postdoc, Artificial Intelligence for Fetal Ultrasound Imaging





Established in 2018 as a company not-distributing profits

Building AI Excellence Ecosystems in the LMICs for an equitable world in the age of AI



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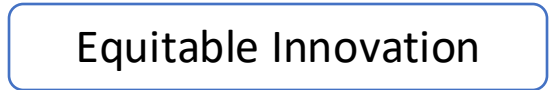
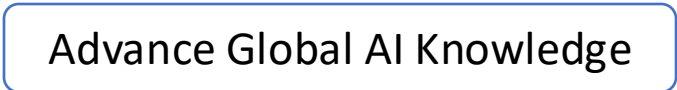
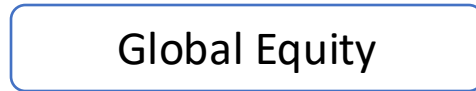
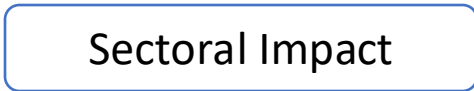
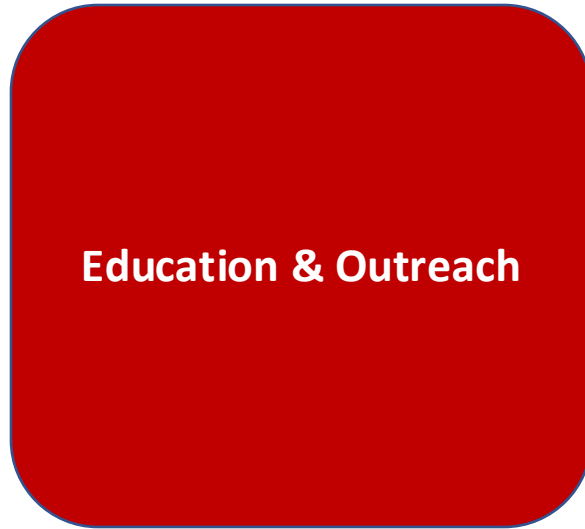
Building AI Excellence Ecosystems in the LMICs for an equitable world in the age of AI

Nepal's first multidisciplinary AI Center of Excellence

Vision

Improving Lives of People through scientific research and innovation

Building an Ecosystem: Through Three Pillars



NAAMII

Building an Ecosystem: Through Three Pillars



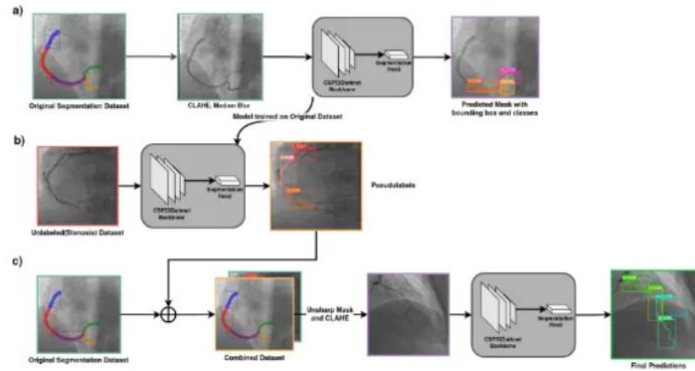
Scientific Research: Autonomous Research Groups



TOGAI (Transforming Global Health with AI)

TOGAI builds intelligent health technologies for low-resource settings. In a world where over 4.5 billion people lack access to essential healthcare, TOGAI tackles critical gaps in diagnostics, specialist access,...

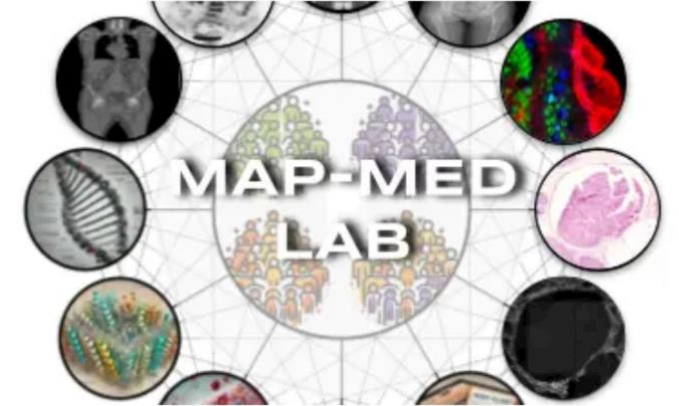
Lead: Dr. Bishesh Khanal



BBMMLL (B Bhattarai Multi-Modal Learning Lab)

The B Bhattarai MultiModal Learning Lab is at the forefront of developing robust and interpretable machine learning algorithms. Our mission is to pioneer algorithms that can reason across complex,...

Lead: Dr. Binod Bhattarai



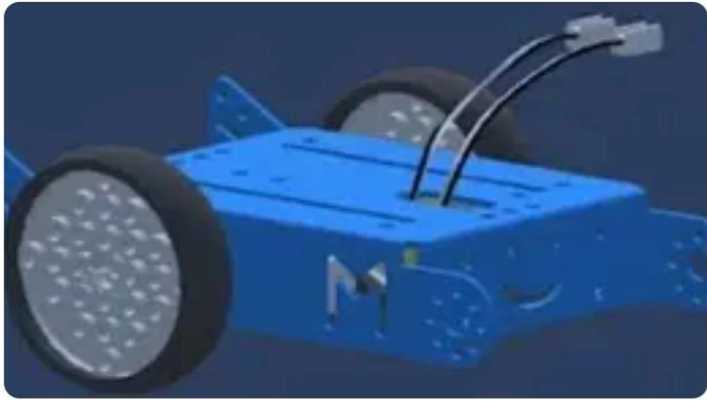
MAPMED (Multimodal Medical Data Analysis for Precision Medicine Lab)

MAPMED focuses on multimodal medical data analysis for decision support systems in radiomics and precision medicine. We specialize in analyzing multimodal medical imaging data, including PET, CT, MRI, and...

Lead: Dr. Taman Upadhaya | Dr. Suman Raj Bista



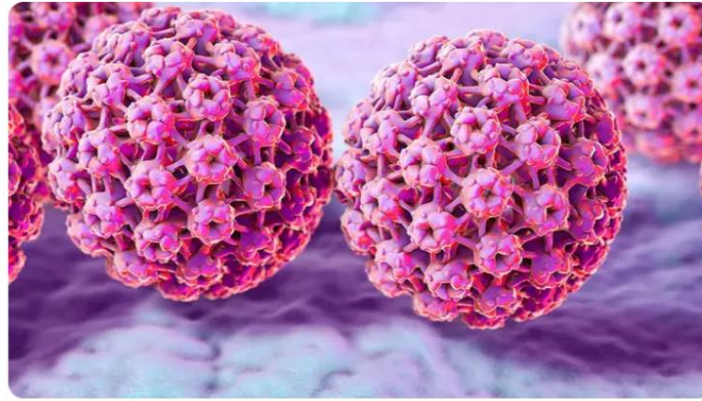
Scientific Research: Autonomous Research Groups



PUSHVIC (Providential Use of Spatial and Human Visual Computing)

PUSHVIC is at the forefront of research in Augmented Reality (AR), Robotics, and Computer Vision. We explore spatial computing and human visual perception to bridge the fundamental research to real-world...

Lead: Dr. François Rameau | Dr. Danda Pani Paudel



CGL (Computational Genomics Lab)

CGL applies bioinformatics and machine learning to tackle pressing challenges in disease biology. Our research focuses on understanding the genomics of communicable and non-communicable diseases, wit...

Lead: Dr. Raunak Shrestha



Agri AI (A²) Innovation Lab (AI for Conscious Living and Sustainable Agriculture)

A² Innovation Lab integrates cutting-edge technology with traditional farming wisdom to develop resilient, sustainable agricultural systems. Our mission centers on three foundational pillars: Climate-Smart Agricultur...

Lead: Dr. Bipendra Basnyat



Research Groups Leb by: Adjunct Faculties (Borderless Groups)



Dr. Bishesh Khanal

Director / Research
Scientist



Dr. Ajad Chhatkuli

Adj. Research
Scientist



Dr. Binod Bhattarai

Adj. Research
Scientist



**Dr. Danda Pani
Paudel**

Adj. Research



Dr. Francois Rameau

Adj. Research
Scientist



Dr. Nabin Koirala

Adj. Research
Scientist



**Dr. Prashna K
Gyawali**

Adj. Research



Dr. Raunak Shrestha

Adj. Research
Scientist



**Prof. Dr. Sabita
Maharjan**

Adj. Principal Research



Dr. Sharib Ali

Adj. Research
Scientist



Dr. Suman Raj Bista

Adj. Research
Scientist



Dr. Taman Upadhaya

Adj. Research
Scientist



Dr. Kiran Raj Pandey

Clinical Research
Scientist



Dr. Bipendra Basnyat

Adj. Research
Scientist



Dr. Buddhi Pathak

Adj. Research
Scientist

ETH Zurich, Switzerland; INSAIT, Bulgaria; University of Aberdeen, UK;

University of Leeds, UK; University of Oxford, UK;

Imperial College London, UK; KAIST, Korea; Yale, USA; UCSF, USA;

University of Oslo, Norway; ...

Research Contributions

Published >75 research articles including Nature Digital Medicine, BMJ, MICCAI, CVPR, ECCV, NeuRIPS, MeDIA, TMI, ...

Trained > 80 research staffs, supervised 5 Msc theses, PhD supervision (3, degrees from US;Spain;Germany), 2 Resident Doctor theses, 5 undergrad final year projects

Many top venues publications: **1st time from Nepal**

Won International Scientific Challenges competed by **top University labs globally**



Outline

Resource-Constrained Settings in Healthcare

Health AI in Resource-Constrained Settings with Examples from Nepal

Trustworthy AI in Healthcare

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Resource-Constrained Settings in Healthcare

Health AI in Resource-Constrained Settings with Examples from Nepal

Trustworthy AI in Healthcare

Resource-constrained Settings in Healthcare

Lack of experts

- Lack of medical doctors, radiologists in primary and community health care settings
- Overburdened Tertiary Health care centers (Big hospitals in urban centers)

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Other kinds of Resource-constraints?

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- Neglected Diseases
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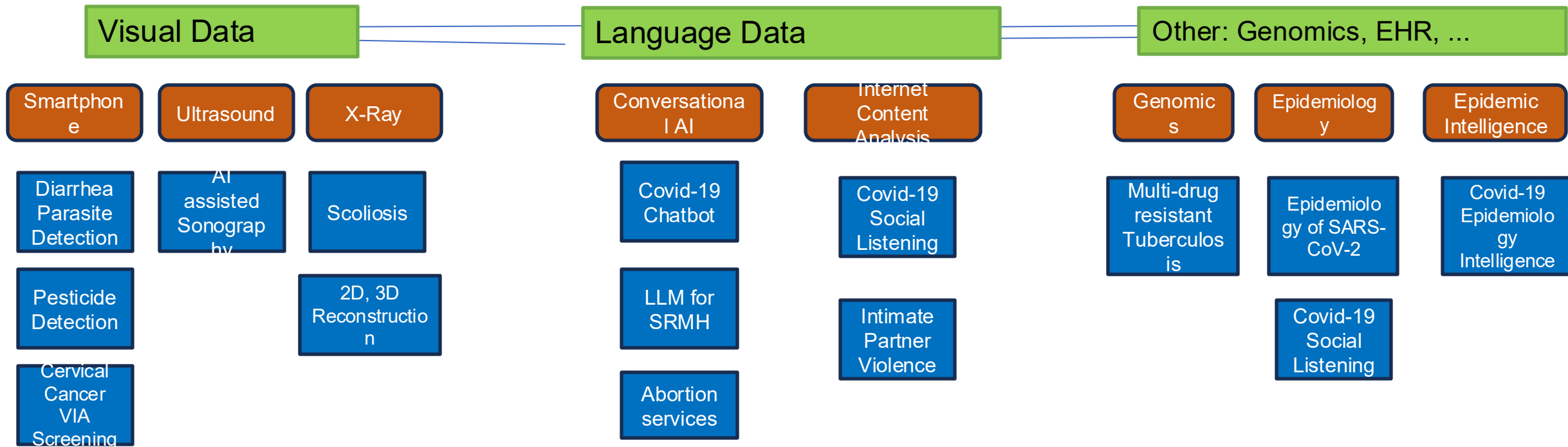
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Trustworthy AI in Healthcare

TransfOrming Global health with AI (TOGAI)



Dental Hospital (with startup) OPG images auto-analysis
 Telemedicine & AI integration in a hospital in Kathmandu:

- oral cancer
- otitis media
- Glaucoma and other eye diseases

TOGAI Themes

Empowering general-public for prevention and early detection

Broadening the scope of health services in primary and community health centers

Inventing new technology to enable health interventions previously not possible

Population-based studies to understand biology & for public health

Bringing access to information, quality health services, and rights to EVERYONE

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Pesticide Estimation with Low-cost Paper Device & AI App

Pesticides in Vegetables & Fruits

- **Big problem in Nepal**

What if:

- we go to pharmacy & buy a kit
- Grind vegetables
- See results of kit on Smartphone

Khanal, B., Pokhrel, P., **Khanal, B.**, & Giri, B. (2021). *Machine-Learning-Assisted Analysis of Colorimetric Assays on Paper Analytical Devices*. ACS omega,

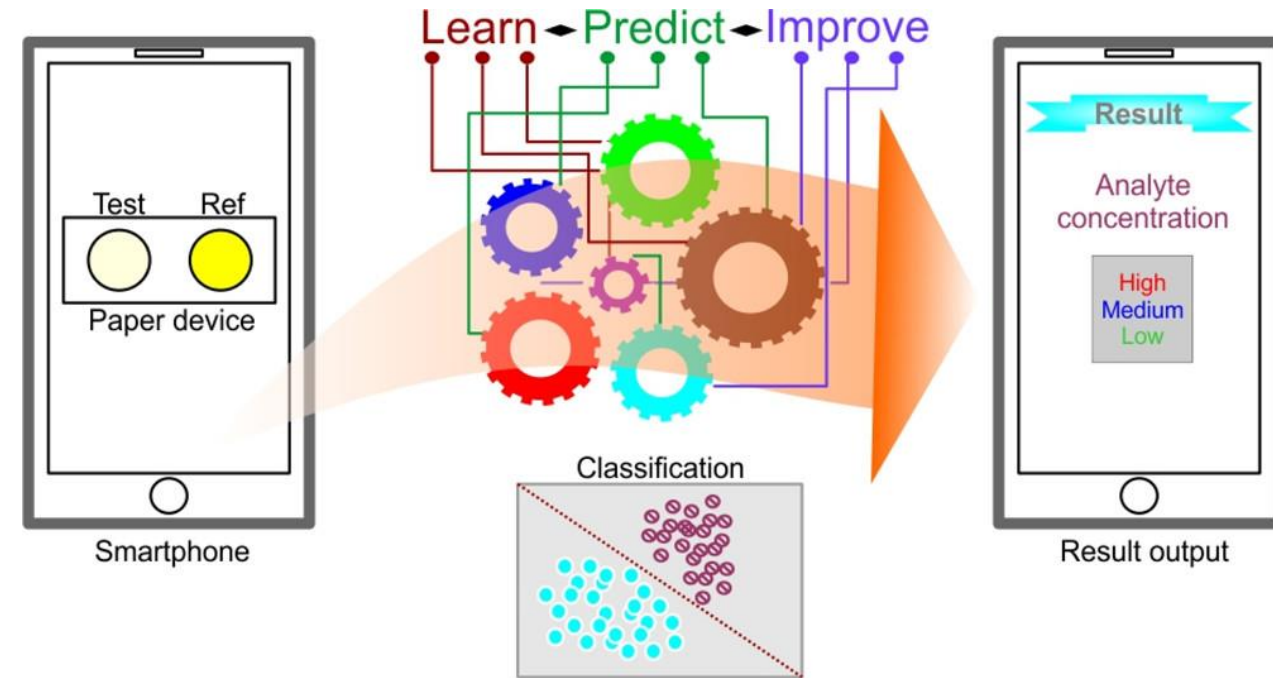
Pesticide Estimation with Low-cost Paper Device & AI App

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Pesticide Estimation with Low-cost Paper Device & AI App

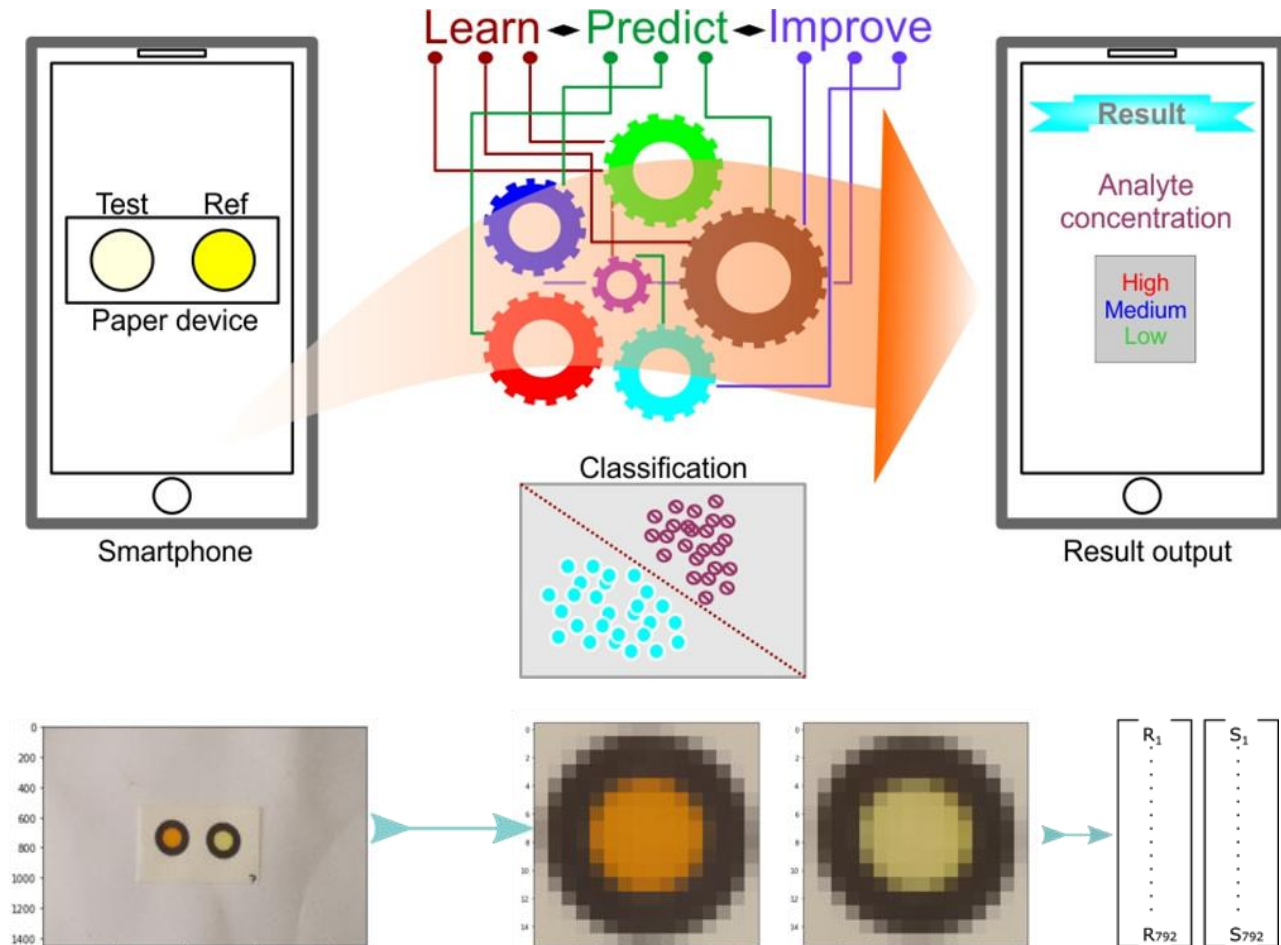
Pesticides in Vegetables & Fruits

- **Big problem in Nepal**

What if:

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This could be possible for major family of pesticides!



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AI-assisted Cervical Cancer Screening with Visual Inspection

Cervical Cancer

- Major type of cancer for women in Nepal (& many LMICs)
- Preventable if identified in pre-cancerous stage
- Can be cured if in early stage
- Visual Inspection with Acetic acid (VIA) most common screening in low-resource

Problem

- Must screen large fraction of the women population but lack of experts

One Part of the Solution

- AI to assist non-experts (e.g. FCHVs, nurses) to do VIA more objectively & accurately

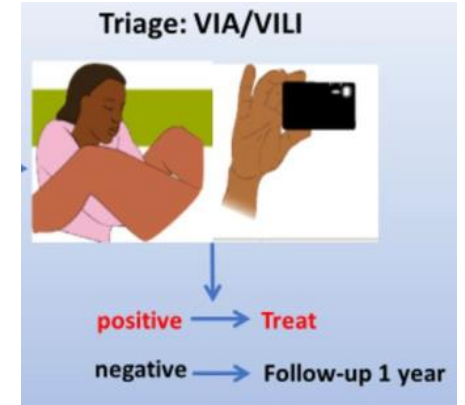
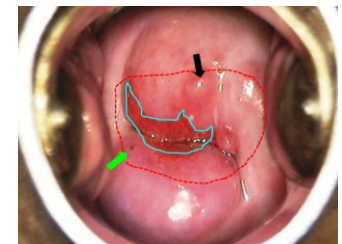


Image Source: Grohar D, et al. Scaling up community-based cervical cancer screening in Cameroon employing a single visit approach. IJGC 2020.



Poudel, K., Poudel, L., Shakya, P.R., Poudel, A., Shrestha, A. and **Khanal, B.**, 2024. *AI-Assisted Cervical Cancer Screening*. arXiv preprint arXiv:2403.11936.
Shrestha, A., Poudel, L., **Khanal, B.**, Poudel, K., Shakya, S., Timsina, P., Shakya, P., Shrestha, S. and Paneru, B., 2024. *Community-based Screening of Cervical Cancer in an Urban Setting in Nepal: A Cross-sectional Study*. Kathmandu Univ Med J, 88(4), pp.413-8.

Ultrasound (US) Imaging



Philips Lumify



Clarius



GE Vscan



Healcerion SONON



Butterfly Network iQ

Advantages

- Portable
- Low-cost [Few Lakhs]
- High temporal resolution
- No radiation

Ultrasound (US) Imaging



Advantages

- Portable
- Low-cost [Few Lakhs]
- High temporal resolution
- No radiation

Challenges

- Limited Field of View
- Operator dependent
- High level expertise required

AI-Assisted Ultrasound (US) Imaging



- Consistency across operators
- Reliable, fast & easy diagnosis
- Enable Non-experts to do US imaging

US Imaging: Need to find right views -> detect -> measure, real-time

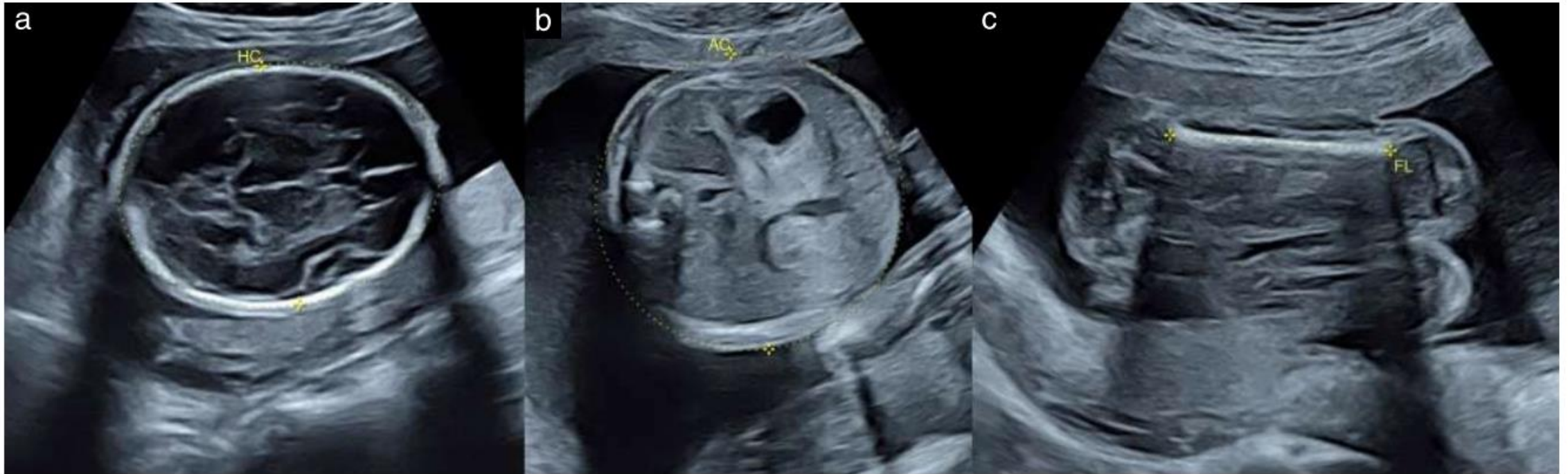


Figure 1 Standard fetal biometry. Sonographic measurements of: (a) head circumference (HC), (b) abdominal circumference (AC) and (c) femur length (FL).

US Imaging: Need to find right views -> detect -> measure, real-time

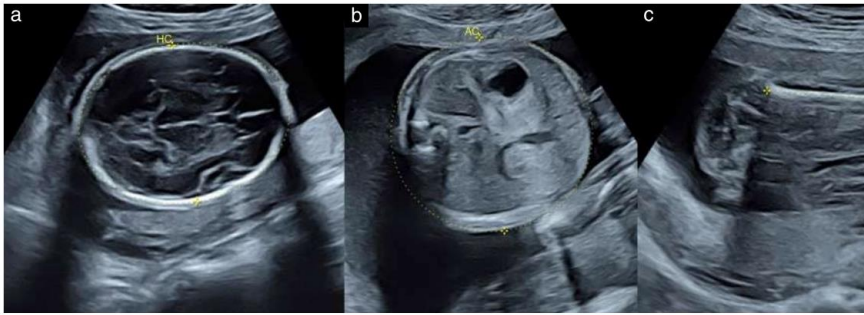
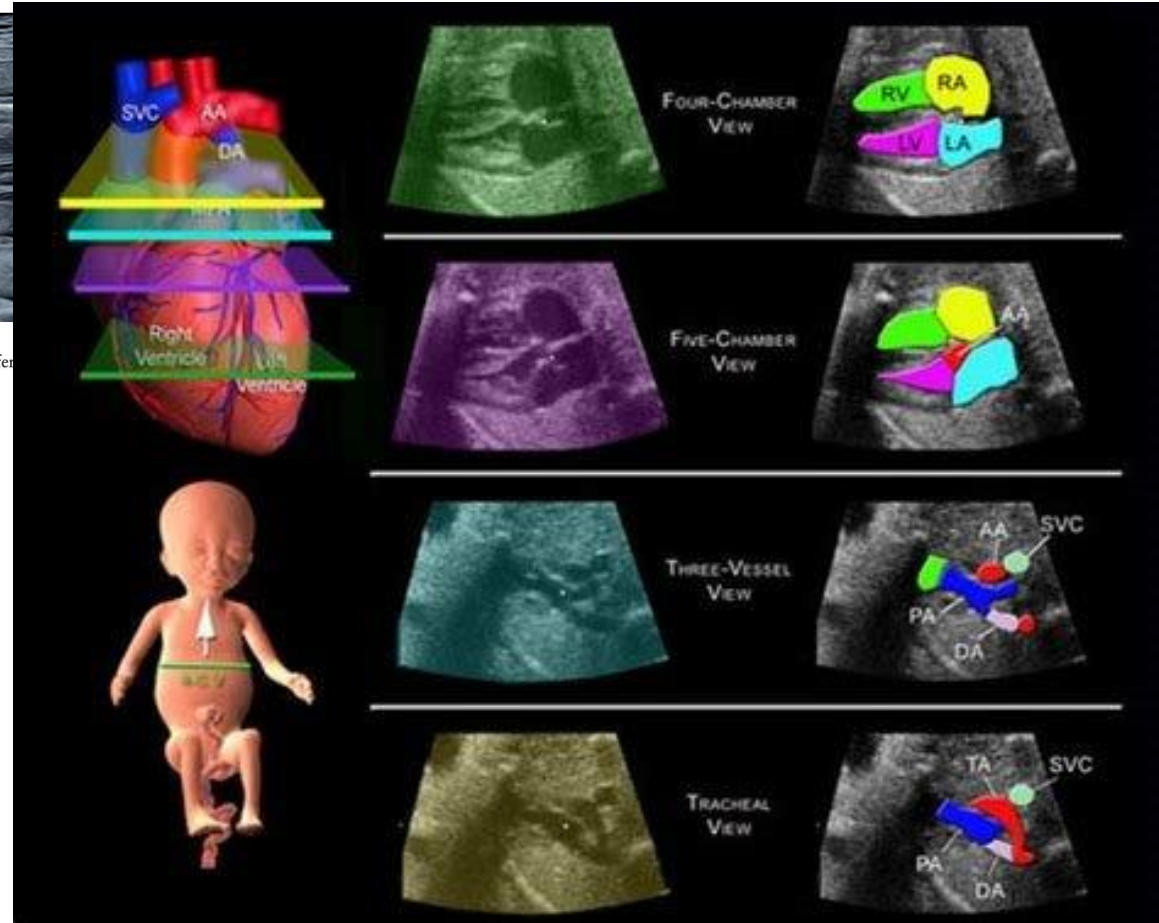


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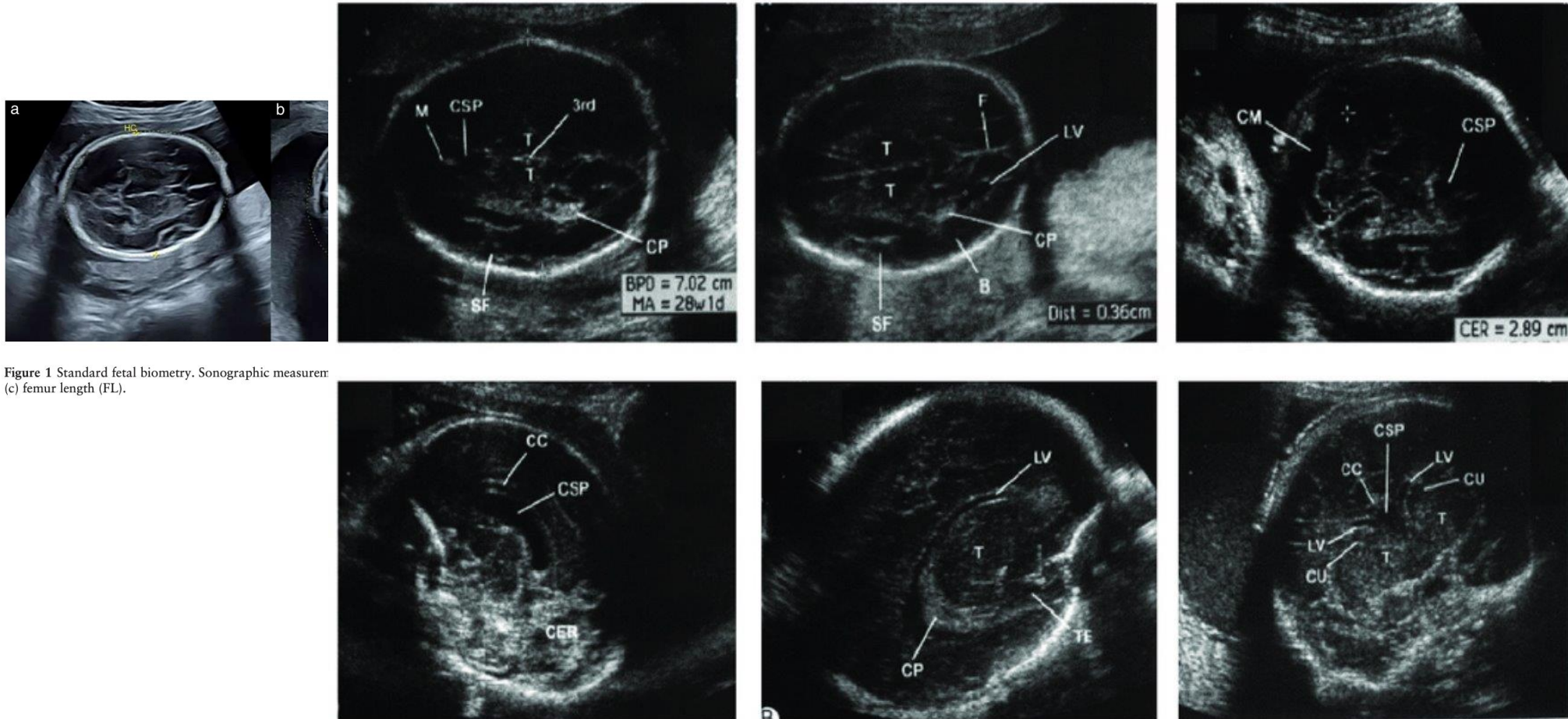


Figure 1 Standard fetal biometry. Sonographic measures (c) femur length (FL).

Samples of the six fetal brain standard planes.

How do we bring AI to the picture?

Automatic view classification and measurements: probe handling by experts

- **Most common and many models proposed for various anatomy and anomaly**

Guidance to non-expert users to find right views and aid (or auto) measurements

- **Relatively unsolved and many open problems**

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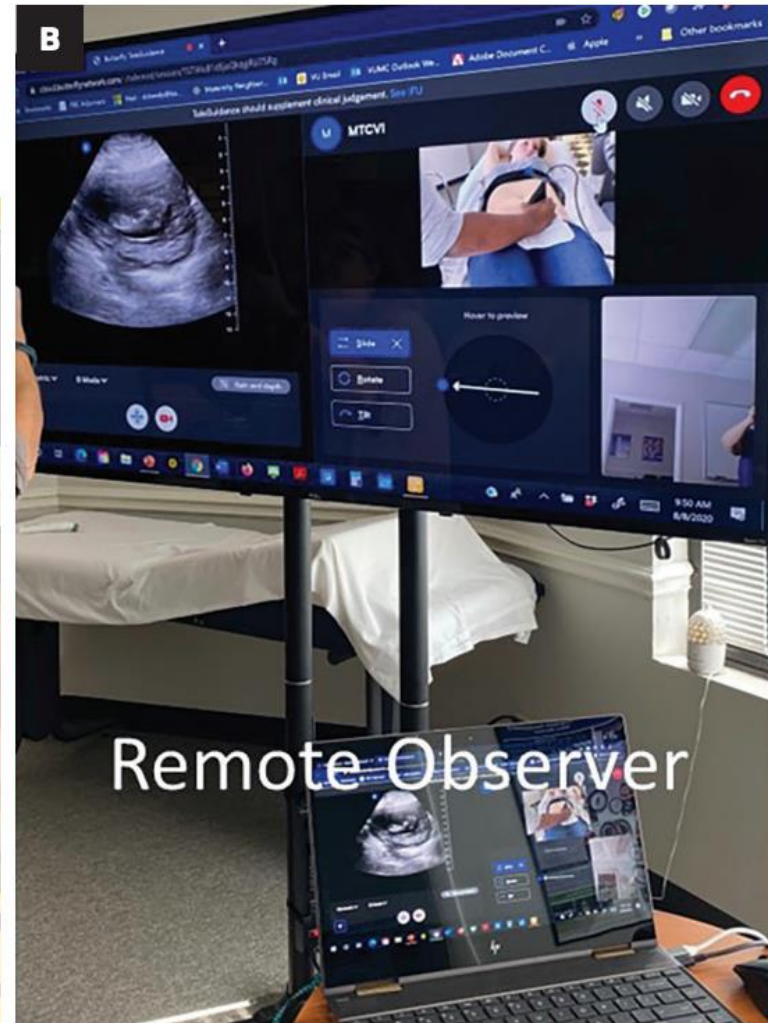
Guidance to non-expert users to find right views and aid (or auto) measurements

- **Relatively unsolved and many²² open problems**

Can we just take videos by sweeping the probes everywhere and then analyse?

Teleradiology Solution ?

Figure 1. Use of a handheld ultrasound unit by a local sonographer (A), while a remote instructor observes the sonographer via video and identical screen in real time. (B)



Diana L. Dowdy, and Robert D. Harris (2024). Global Health Imaging. Applied Radiology.

Teleradiology Solution ?

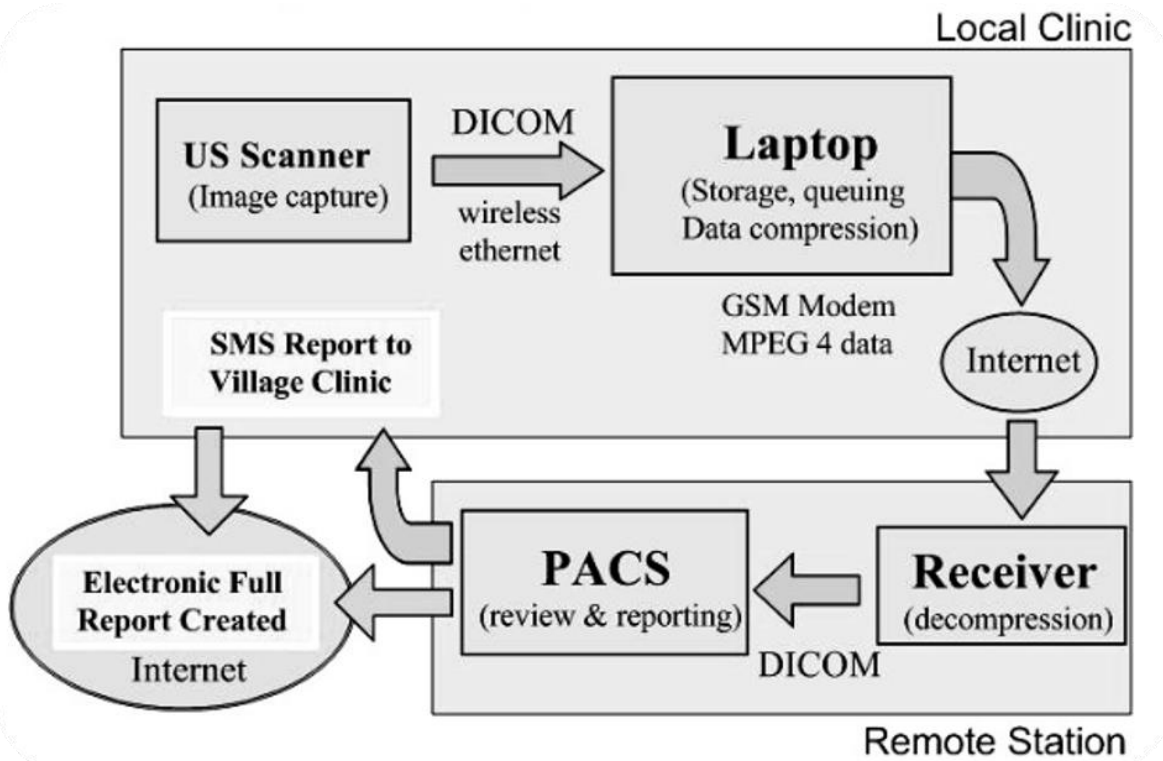
Hard to scale!

Good internet connection often not available (where this solution is required)

Need for experts to sync working hours with remote health workers for real-time feedback

Experts typically already burdened

Teleradiology Solution Explored in Early 2010s

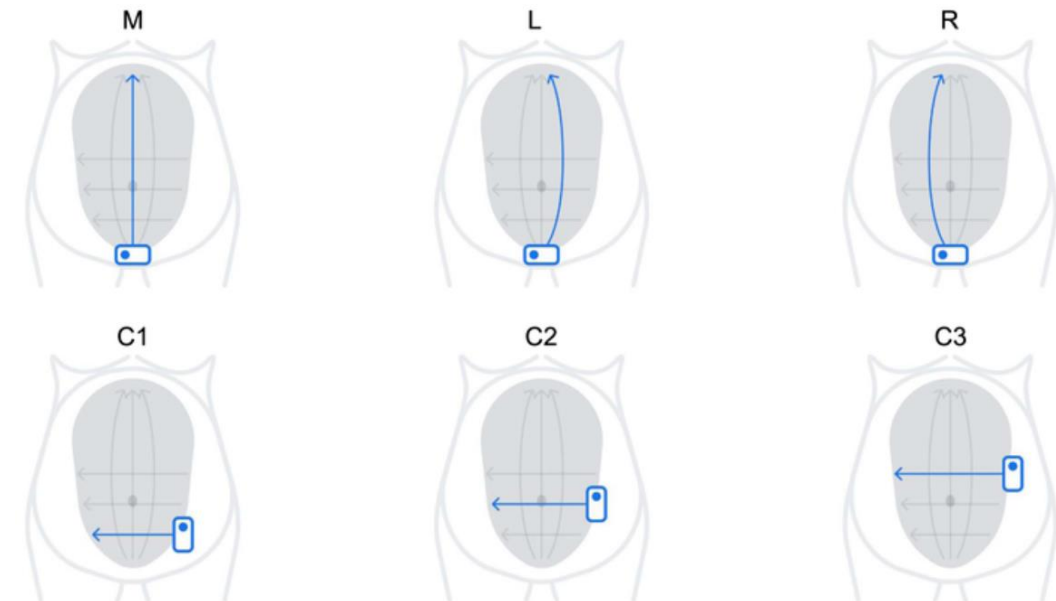


Destigter, Kristen *et al* (2011). Low-Cost Teleradiology for Rural Ultrasound. Proceedings - 2011 IEEE Global Humanitarian Technology Conference, GHTC 2011. <https://www.philips.com/c-dam/corporate/about-philips/sustainability/healthy-people/fabric-of-africa/programs/Low-cost-teleradiology.pdf>

Blind Sweep Videos; First Protocols by Imaging the World, 2011

Blind-sweep by non-experts using easy to follow protocol

Analysed later by experts



Transverse Center Pelvis

Midline (Pelvic Bone to Breast Bone)

Notch towards Patient's Right

Destigter, Kristen et al (2011). Low-Cost Teleradiology for Rural Ultrasound. Proceedings - 2011 IEEE Global Humanitarian Technology Conference, GHTC 2011.

AI-Assisted Task-shifting for Rural Obstetrics Ultrasound

PI: Bishesh Khanal

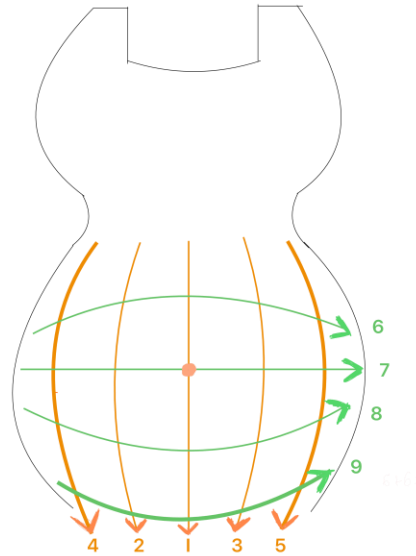
Gates Foundation

Multi-country research

- Africa and South Asia
- AI-powered task shifting
- Funded by: Gates Foundation

Data Collection

- 2000 fetal Blind Sweep ultrasound videos
- Big teaching hospital in urban setting + community health center in a rural setting
- Data collection using 8 "blind sweeps"
- "blind" => following specific directions without considering fetal positions



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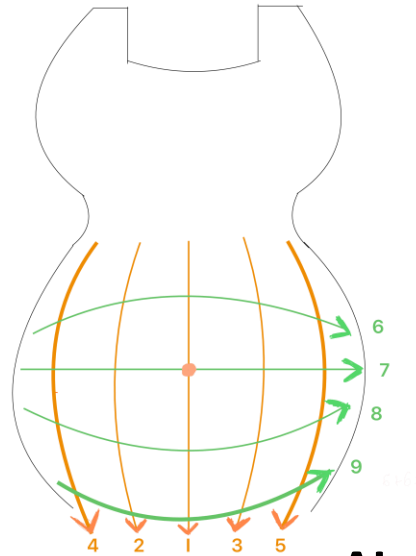
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AI-powered Quality Assessment for Blind Sweep

- Real-time high-quality acquisition of blind sweep



GE HealthCare



NAAMII

AI-Assisted Task-shifting for Rural Obstetrics Ultrasound



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Maharajgunj
Medical Campus

PI: Bishesh Khanal; Co-I: Pradeep Raj Regmi

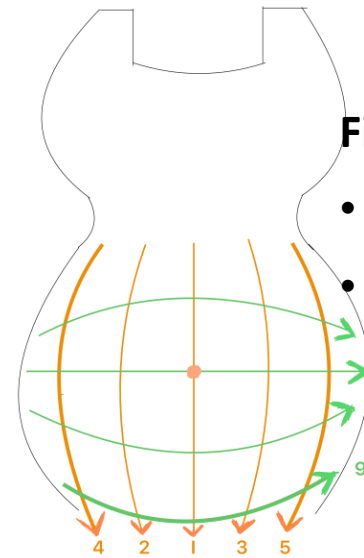
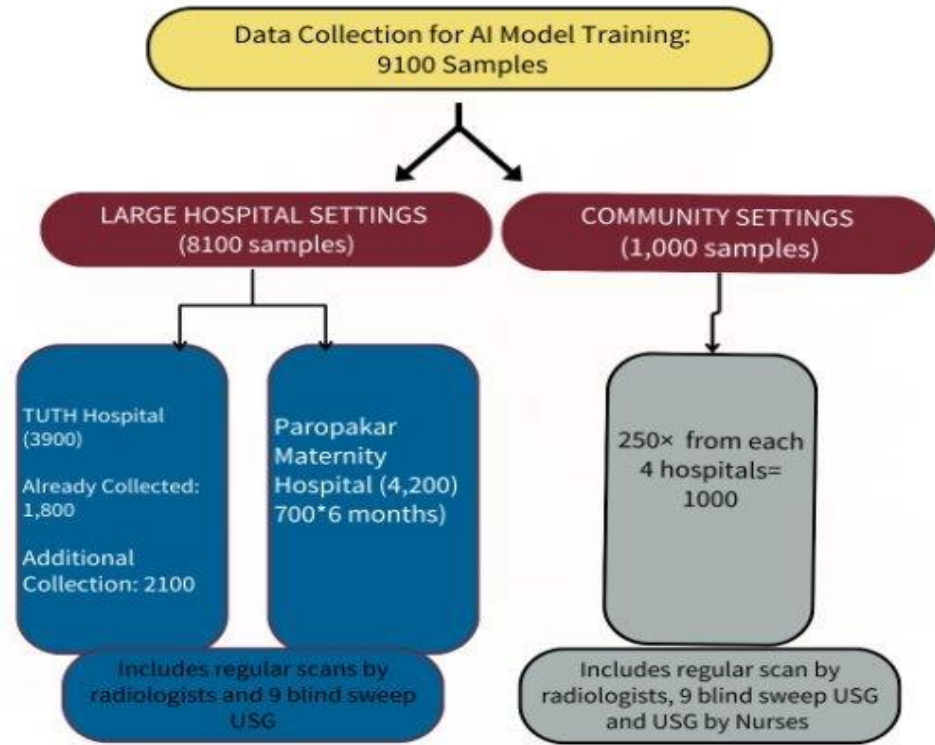


Fig 1. 9 sweep protocol

Abnormalities Selected and AI tasks

First trimester:

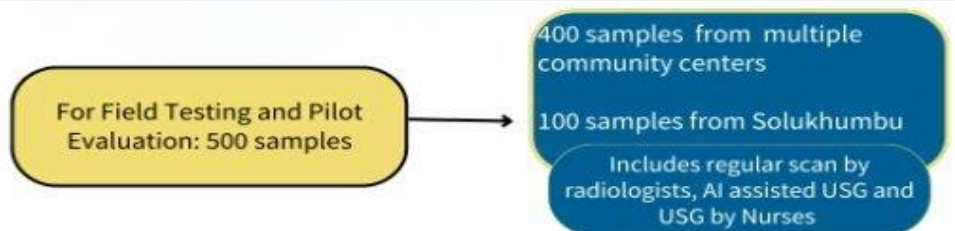
- Single vs multiple pregnancy
- Ectopic vs non-ectopic

Second trimester:

- Placental location
- Cervix Shape

Third trimester:

- Same as 2nd + Fetal orientation



Objective

- Improve FUS in primary and rural health centers
- AI-powered task shifting
- Automatically identify life-saving obs.emergencies

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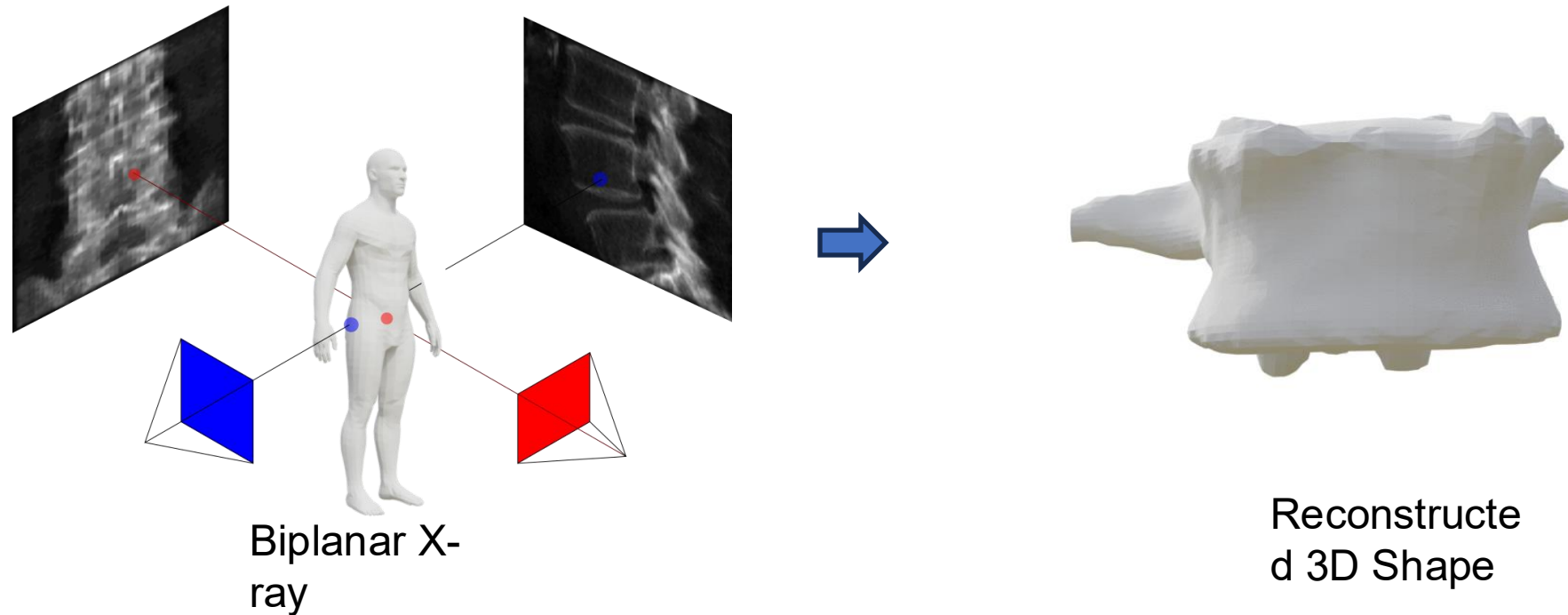
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- CT Scans and MRIs are expensive; more advanced expensive not available
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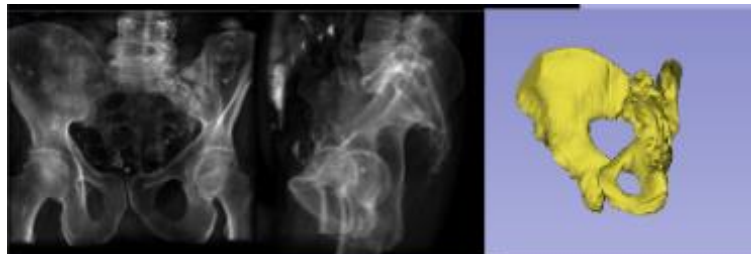
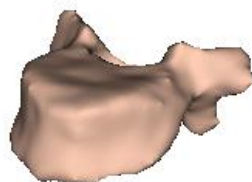
Bi-planar X-ray to 3D reconstruction



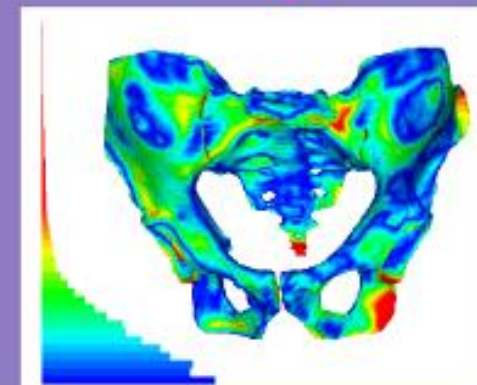
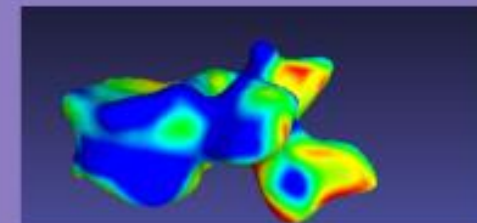
Augments low cost, low radiation X-ray device with CT-like 3D visualization

Improved diagnosis, surgery planning and navigation, better biomarkers

Alternate to Expensive/Unavailable CT-Scan?



How do current state of the art perform in public dataset? (Not as well as reported.)



Error: Red, Green, Blue color denote positive, zero and negative distance to ground truth. Avg reconstruction error 2.5 mm Trained on the challenging public Vertebra Dataset (VerSe¹).

Mahesh Shakya & **Bishesh Khanal**. Benchmarking X-ray 2D-3D reconstruction models and moving towards clinical translation. Neural Information Processing Systems (NeurIPS) Datasets and Benchmark Track, 2023..

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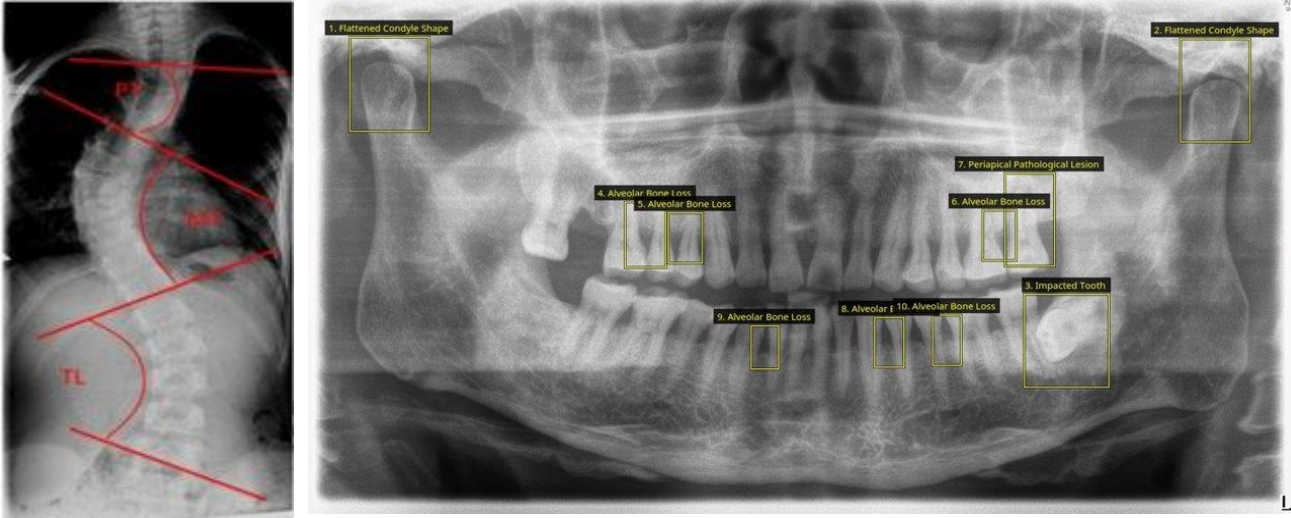
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X-ray Imaging



Advantages

- Portable
- Low-cost
- Widely available

Challenges

- Under-reported

<https://becominghuman.ai/ultrasound-on-a-chip-supercharged-with-ai-the-most-disruptive-technology-in-radiology-b2684b0421aa>

विशेष रिपोर्ट: बालबालिका हुकाउँदा हुने त्रुटिले किशोरावस्थामै बाङ्गिन थाल्यो उनीहरूको हड्डी

- सविना देवकोटा

| मंगलबार, भदौ १, २०७८

दुई वर्षअधिको कुरा हो । भक्तपुर, बालकोटकी १४ वर्षीया लिजा दाहालको शरीर एकाएक अस्वाभाविक देखिन थाल्यो । कताकता बाङ्गो भएर हिंडेजस्तो देखिने उनको शरीर बस्दा पनि कुप्रो परेर बसेजस्तो देखियो ।



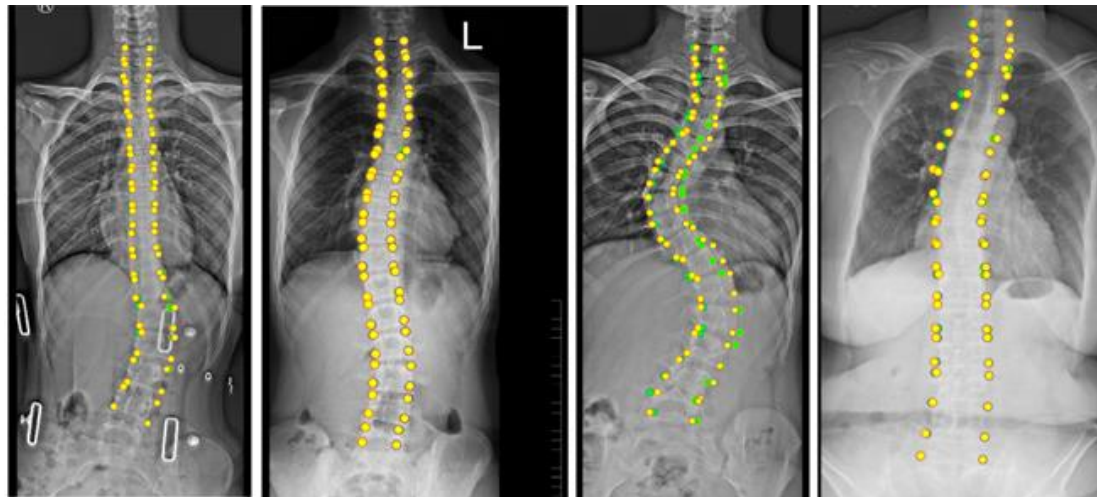
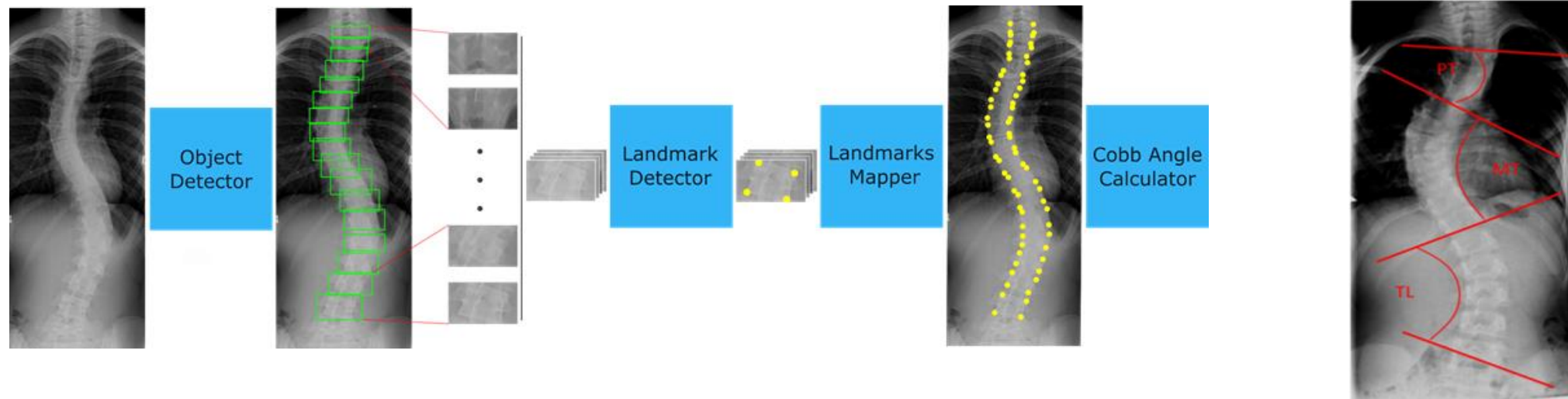
पौडेल भन्छन्, 'स्केरोसिस' जन्मजातै हड्डीमा हुने खराबीले निम्ताउने रोग हो ।' यद्यपि पछिल्लो समय यो रोग जन्मजात मात्रै नभएर लिजालाई झैं अव्यवस्थित जीवनशैली र खानपिनका कारण अधिकांश बालबालिका तथा किशोरावस्थामा देखिन थालेको पौडेल बताउँछन् ।

तिनैमध्येका अर्का एक हुन्, कालिमाटीका १३ वर्षीय सुप्रिम अधिकारी ।

ग्रान्डी, टिचिङलगायत उपत्यकाका विभिन्न अस्पतालहरूमा दाहाल परिवार चहादै गर्दा (एक्स-रे, एमआरआई, सिटी स्क्यान) परीक्षण गरेपछि थाहा भयो, लिजाको मेरुदण्ड ४५ डिग्रीमा बाङ्गिसकेको रहेछ । चिकित्सकहरूले तत्काल

<https://shilapatra.com/detail/64897>

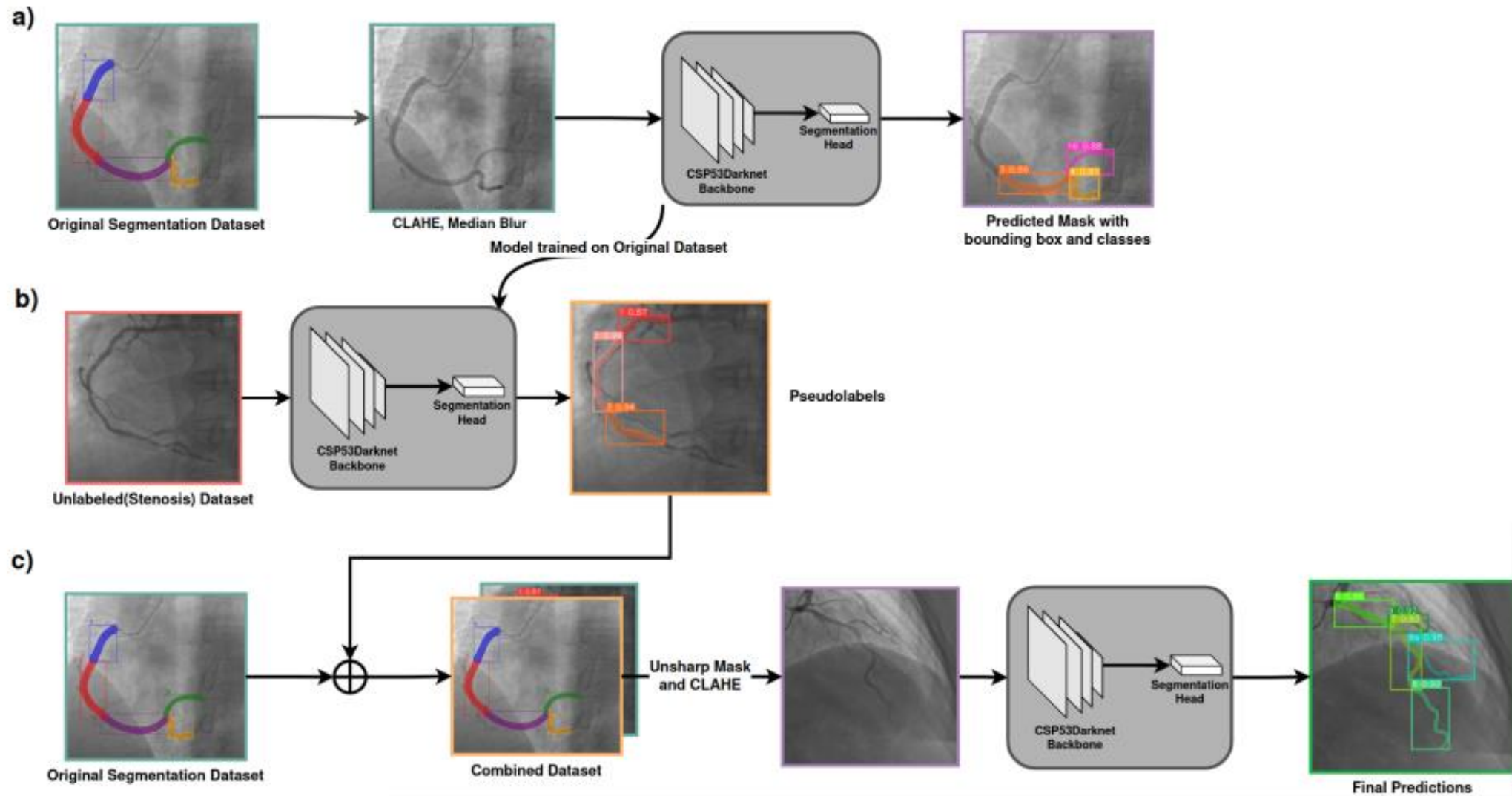
Scoliosis Management: Automatic Cobb-Angle Detection



Scoliosis

- Common in adolescents
- Permanent disability or fatal if untreated
- Cobb angle an important marker
 - Tedious to measure Cobb-angle
 - High inter-rater variability

Arterial Segmentation & Stenosis Detection in X-ray Angiography



Binod Bhattarai
Lab @

Resource-Constrained Settings in Healthcare

Lack of experts

- Lack of medical doctors, radiologists in primary and community health care settings
- Overburdened Tertiary Health care centers (Big hospitals in urban centers)

Lack of devices, algorithms, or technologies

- CT Scans and MRIs are expensive; more advanced expensive not available
- AI: Lack of Data/Internet/compute resources/financial resource

Lack of research and innovation

- Neglected Diseases
- Inability to solve problems quickly: Dengue is killing more & more people in Kathmandu
- Emerging useful technology being inaccessible (e.g. chatbot due to language barrier)

Low-cost Smartphone-sized Microscopes to Detect Parasites?

Easily Deployable

Automated and Scalable

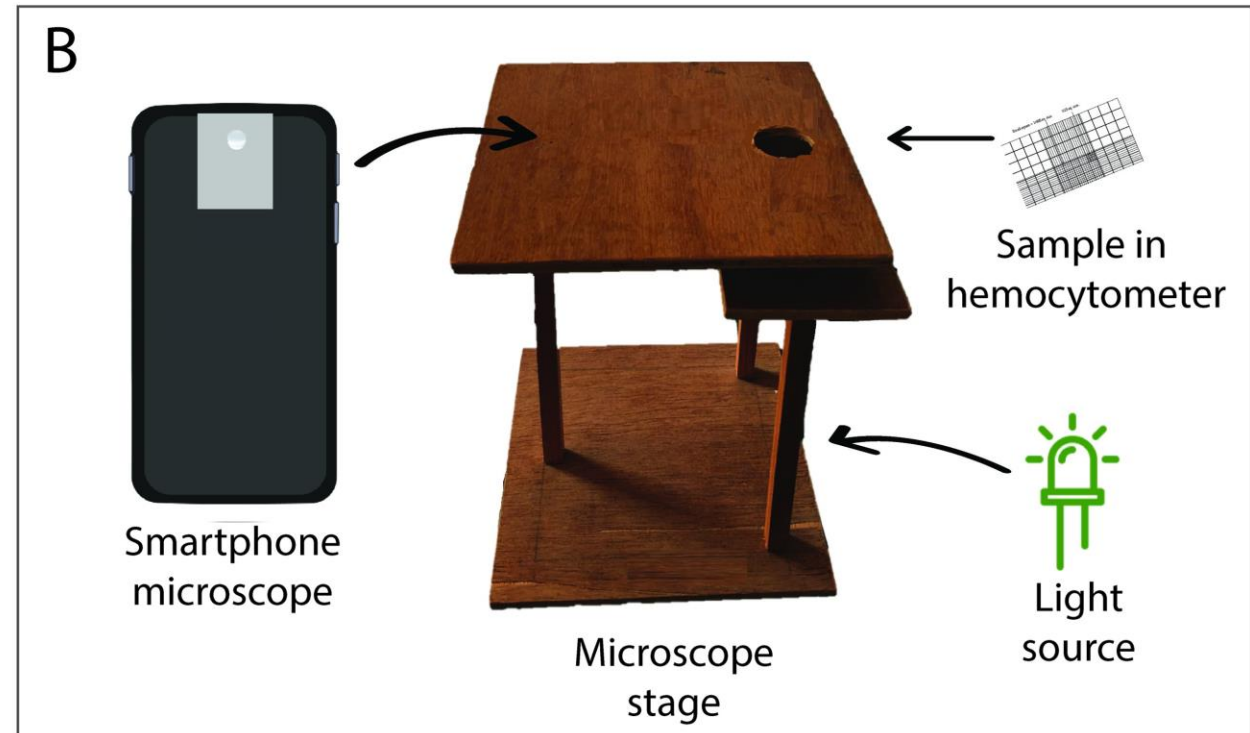
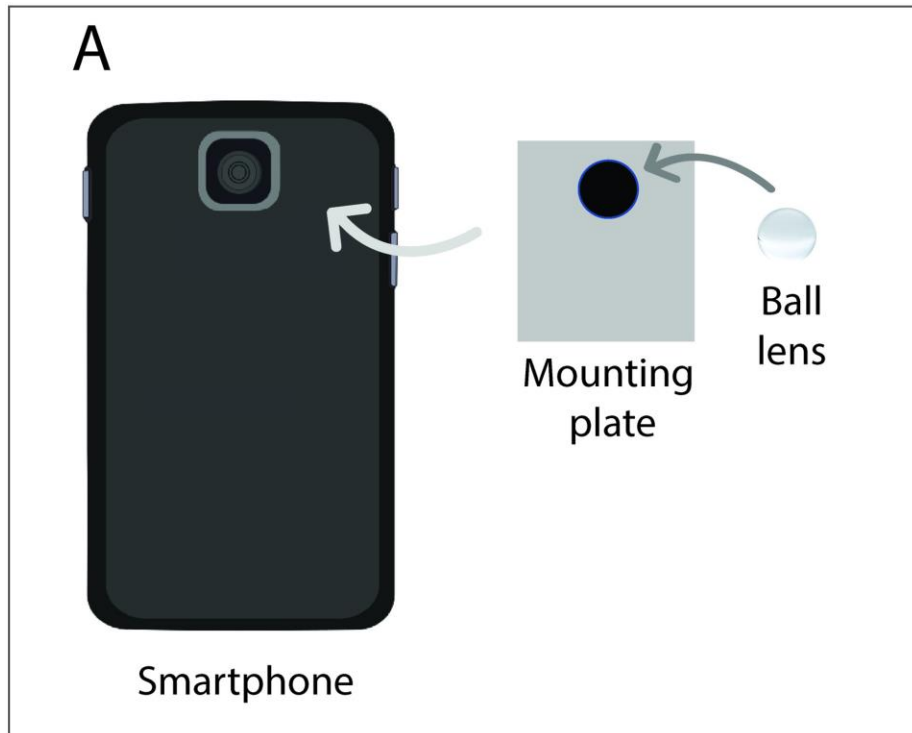
Monitoring consistently across geographies

A smartphone microscopic method for simultaneous detection of (oo)cysts of *Cryptosporidium* and *Giardia*

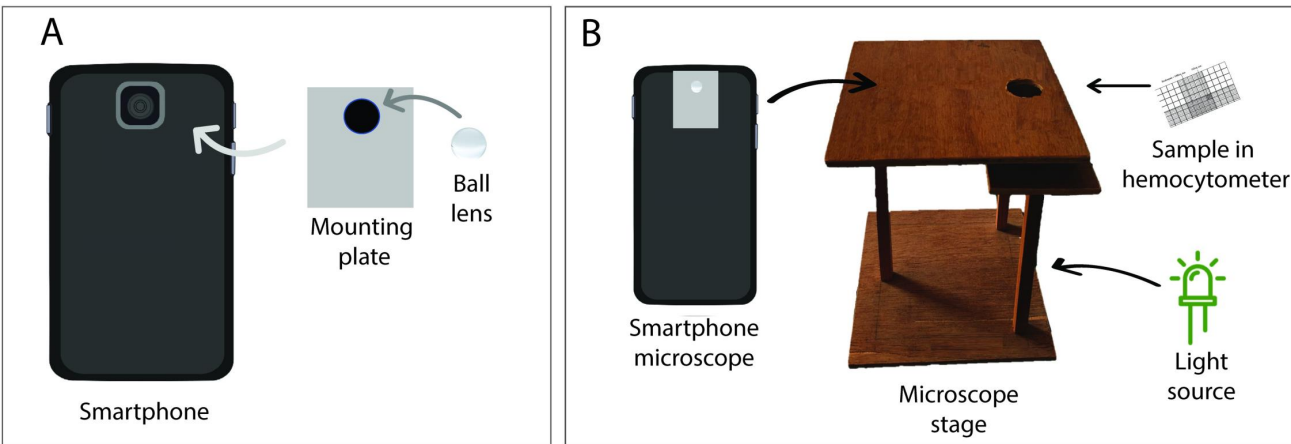
Retina Shrestha, Rojina Duwal, Sajeev Wagle, Samiksha Pokhrel, Basant Giri , Bhanu Bhakta Neupane 

PLOS  **Neglected Tropical Diseases**

Published: September 8, 2020 • <https://doi.org/10.1371/journal.pntd.0008560>



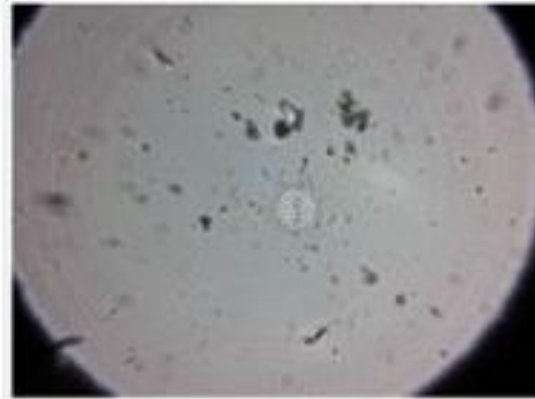
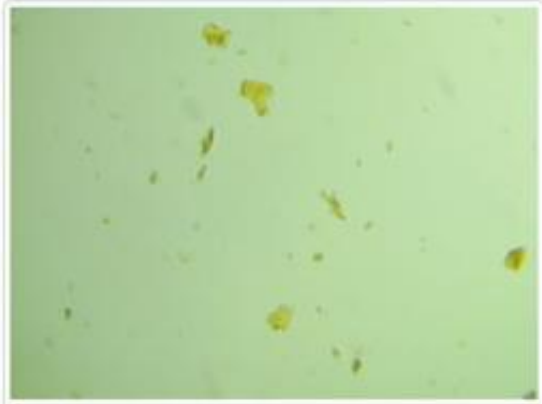
Smartphone Microscopy for Detecting cysts of Parasites



Diameter of ball lens (mm)	Clear field of view (μm)
0.5	114 \pm 6
1	203 \pm 6
2	490 \pm 10

<https://doi.org/10.1371/journal.pntd.0008560.t001>

Traditional Brightfield Microscope vs Smartphone Microscope



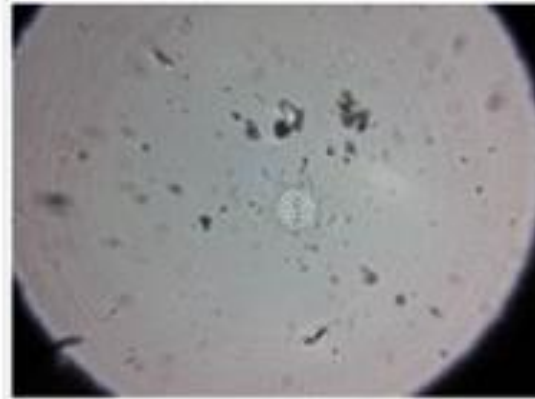
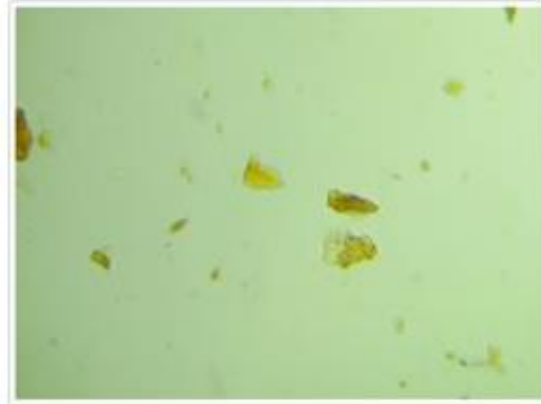
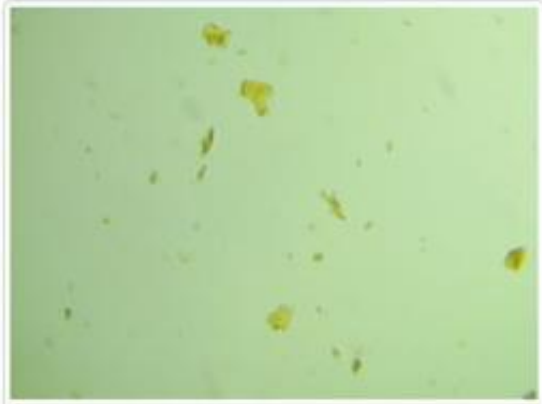
A smartphone microscopic method for simultaneous detection of (oo)cysts of *Cryptosporidium* and *Giardia*

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PLOS Neglected Tropical Diseases

Published: September 8, 2020 • <https://doi.org/10.1371/journal.pntd.0008560>

Microscopes can be Deployed, but Expertise to Detect Parasites?



A smartphone microscopic method for simultaneous detection of (oo)cysts of *Cryptosporidium* and *Giardia*

Retina Shrestha, Rojina Duwal, Sajeev Wagle, Samiksha Pokhrel, Basant Giri , Bhanu Bhakta Neupane 

PLOS  Neglected Tropical Diseases

Published: September 8, 2020 • <https://doi.org/10.1371/journal.pntd.0008560>

AI-powered Smartphone Microscopy

AI Models to Identify the Diarrhea Causing Parasites in Smartphone Microscope Images



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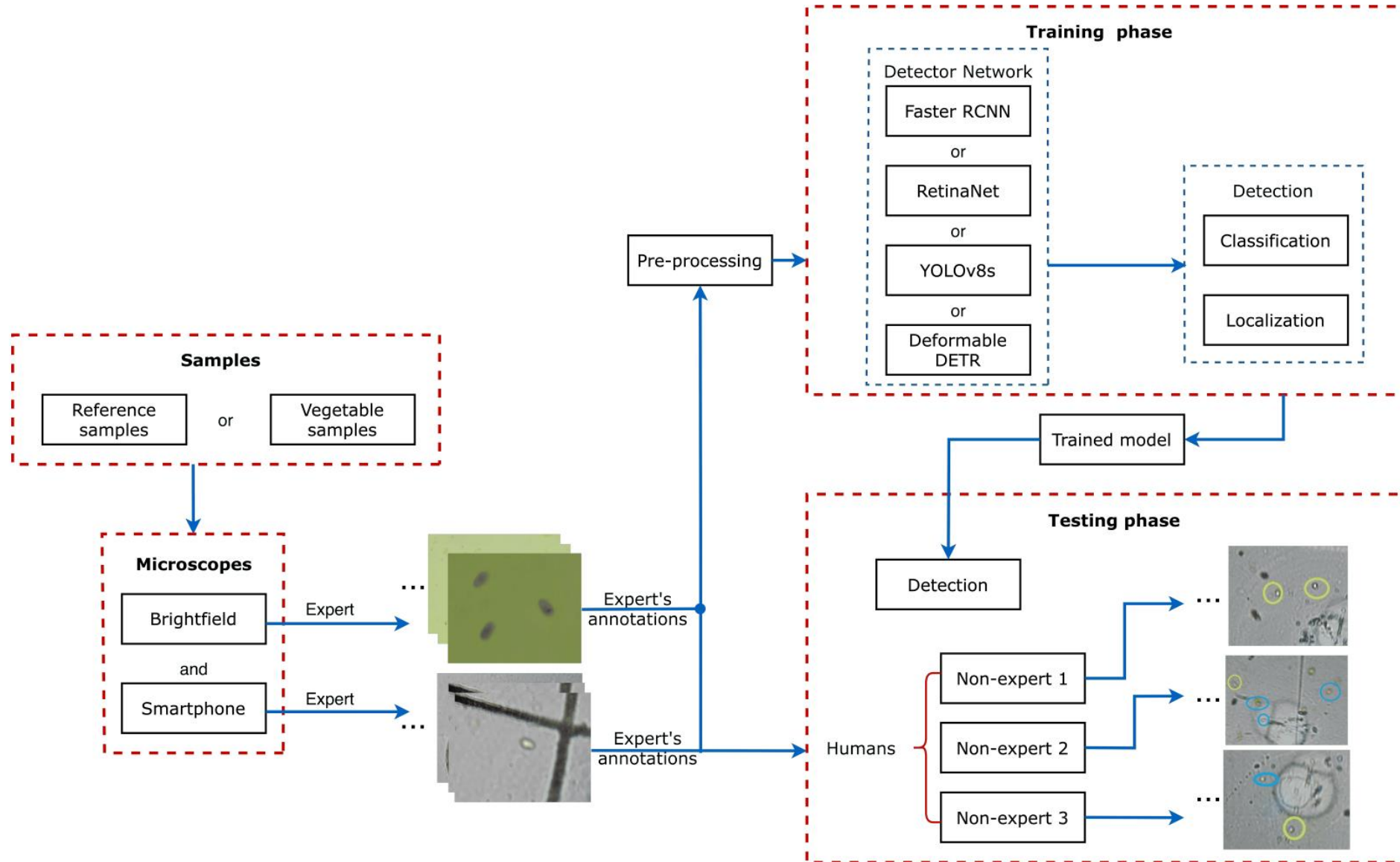
AI-powered Smartphone Microscopy

AI Models to Identify the Diarrhea Causing Parasites in Smartphone Microscope Images

South – South Collaboration (+ in country collaboration) , not so common!



AI-powered Smartphone Microscopy



AI-powered Smartphone Microscopy

Images from reference samples

Images from real vegetable samples

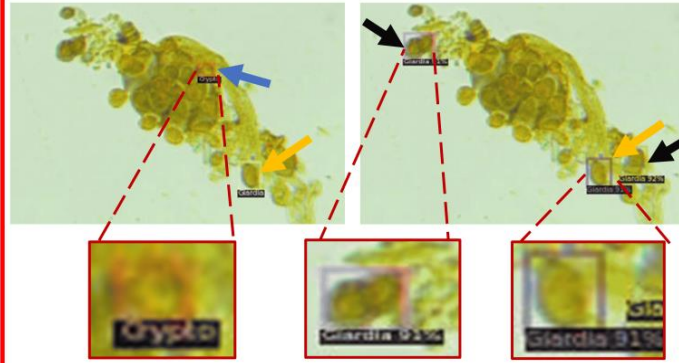
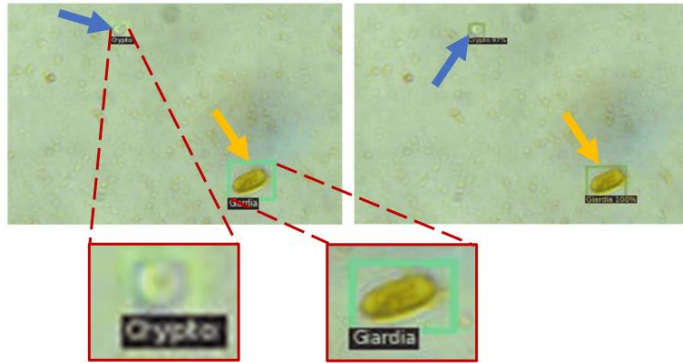
Ground truth

Predicted images

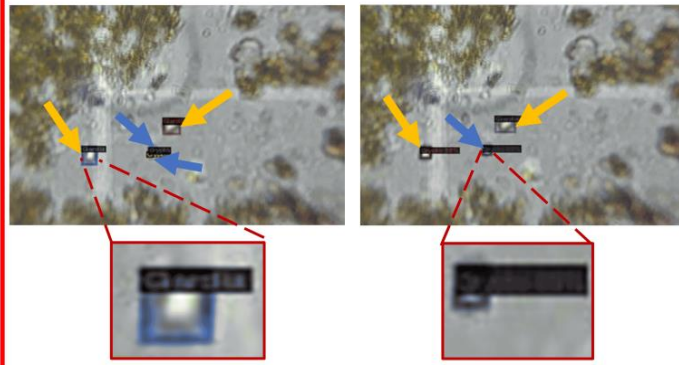
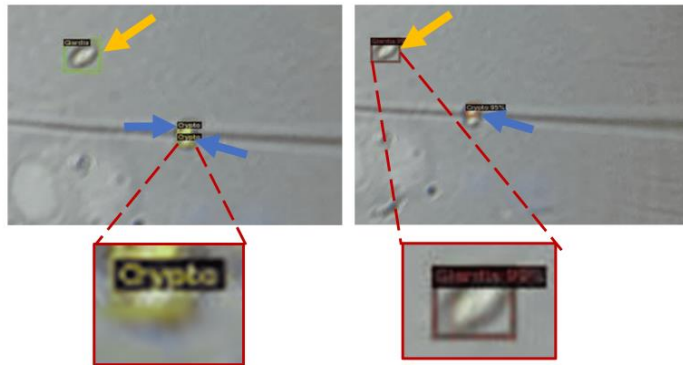
Ground truth

Predicted images

Brightfield microscopy images



Smartphone microscopy images



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AI-powered Smartphone Microscopy

Dataset	No. of images	Microscopes	Giardia's annotation	Cryptosporidium's annotation
Reference sample	830	Smartphone	839	534
		Brightfield	907	502
Vegetable sample	1005	Smartphone	439	796
		Brightfield	344	740
Test (vegetable sample)	193	Smartphone	165	137



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AI-powered Smartphone Microscopy

Dataset	Models	Thresholds	Precision	Recall	F1-score
<i>Giardia</i>					
Reference Sample	Faster RCNN	$c = 0.7, i = 0.4$	0.957 ± 0.014	0.968 ± 0.018	0.962 ± 0.007
	RetinaNet	$c = 0.5, i = 0.5$	0.917 ± 0.017	0.946 ± 0.013	0.931 ± 0.011
	YOLOv8s	$c = 0.4, i = 0.3$	0.954 ± 0.016	0.975 ± 0.010	0.965 ± 0.010
	Deformable DETR	$c = 0.4, i = 0.2$	0.864 ± 0.037	0.870 ± 0.014	0.867 ± 0.021
Vegetable Sample	Faster RCNN	$c = 0.8, i = 0.5$	0.783 ± 0.024	0.901 ± 0.026	0.837 ± 0.005
	RetinaNet	$c = 0.4, i = 0.4$	0.753 ± 0.029	0.927 ± 0.035	0.830 ± 0.024
	YOLOv8s	$c = 0.4, i = 0.3$	0.855 ± 0.037	0.811 ± 0.018	0.831 ± 0.018
	Deformable DETR	$c = 0.4, i = 0.2$	0.636 ± 0.042	0.782 ± 0.063	0.700 ± 0.042
<i>Cryptosporidium</i>					
Reference Sample	Faster RCNN	$c = 0.7, i = 0.4$	0.880 ± 0.024	0.915 ± 0.030	0.897 ± 0.018
	RetinaNet	$c = 0.5, i = 0.5$	0.917 ± 0.025	0.870 ± 0.031	0.893 ± 0.022
	YOLOv8s	$c = 0.4, i = 0.3$	0.890 ± 0.034	0.887 ± 0.031	0.888 ± 0.028
	Deformable DETR	$c = 0.4, i = 0.2$	0.768 ± 0.035	0.808 ± 0.012	0.787 ± 0.015
Vegetable Sample	Faster RCNN	$c = 0.8, i = 0.5$	0.845 ± 0.029	0.835 ± 0.045	0.839 ± 0.024
	RetinaNet	$c = 0.4, i = 0.4$	0.801 ± 0.025	0.851 ± 0.022	0.826 ± 0.023
	YOLOv8s	$c = 0.4, i = 0.3$	0.879 ± 0.052	0.716 ± 0.065	0.788 ± 0.051
	Deformable DETR	$c = 0.4, i = 0.2$	0.642 ± 0.029	0.720 ± 0.054	0.678 ± 0.033



Need for a Larger Dataset and Better Accuracy



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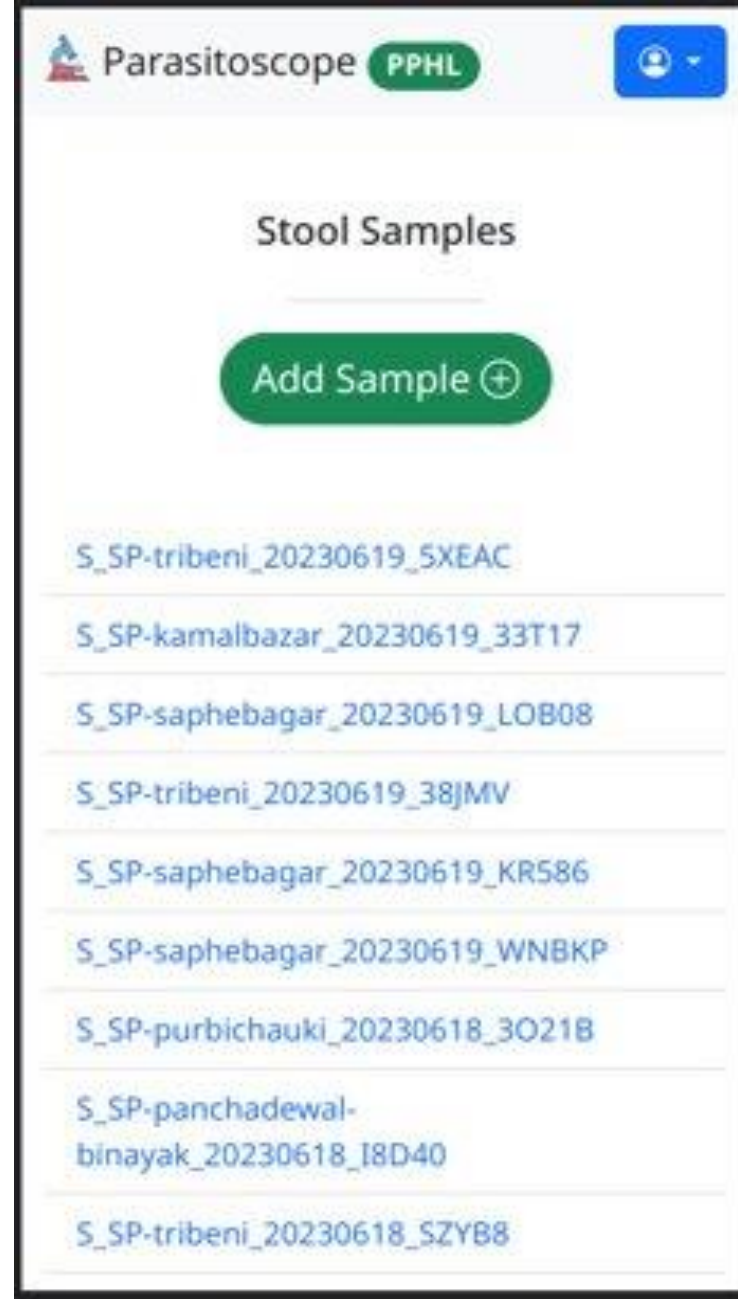
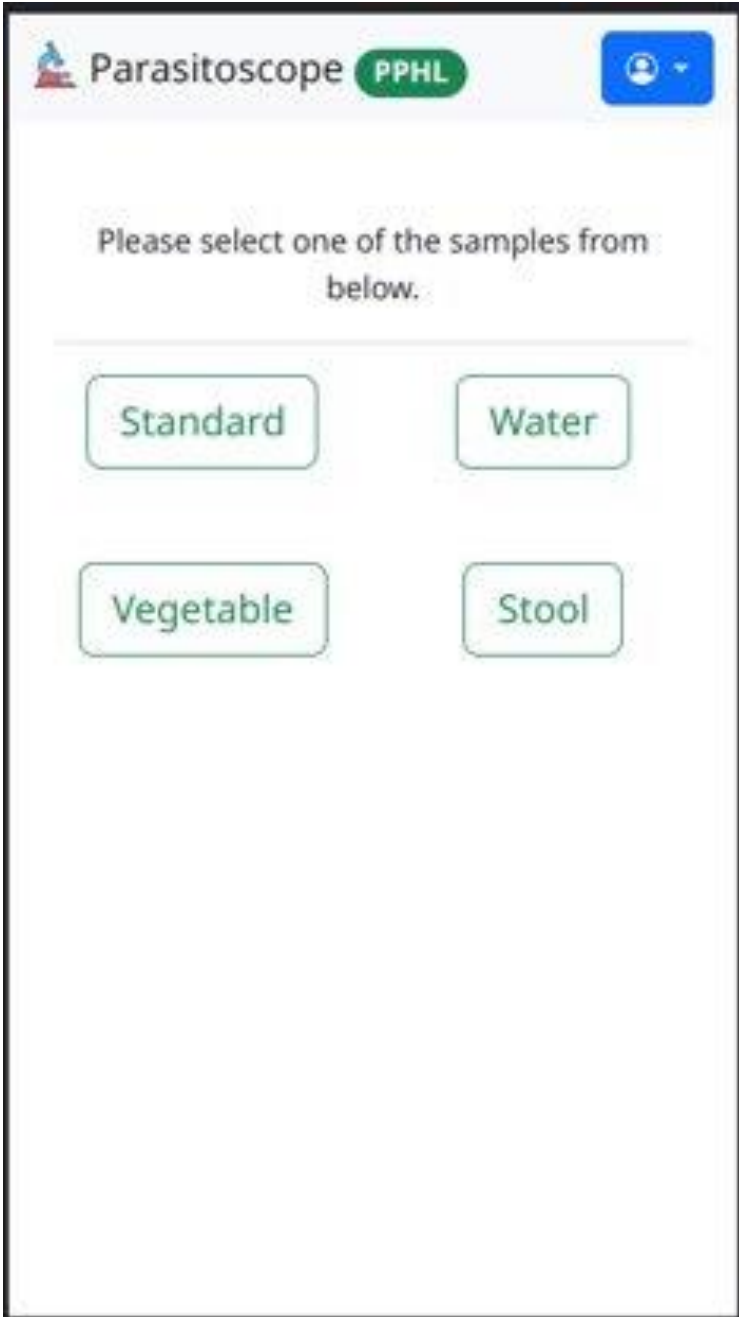


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Parasitoscope: AI-powered Smartphone Microscopy



सामाजिक विकास मन्त्रालय
प्रदेश जनस्वास्थ्य प्रयोगशाला
मधेश प्रदेश, जनकपुरधाम



Parasitoscope PPHL

Add new stool sample

Province*

District*

Municipality/Gaunpalika*

Date of collection*

06/19/2023

Patient's Gender*

Patient's age*

Symptoms*

Stool texture*

Submit

Parasitoscope NAAMII

[Waters](#) / W_BP-kirtipur_20221129_F5K3W

W_BP-kirtipur_20221129_F5K3W

Date of collection Nov. 29, 2022

Province Bagmati Pradesh

District Kathmandu

Municipality/GaunPalika Kirtipur

Ward 6

Locality Jalbinayak temple

Water Type River

Water Use May be irrigation

Latitude 27.658300

Longitude 85.292000

Site Image 

Slide 1

Parasitoscope NAAMII

[Vegetables](#) / V_BP-kathmandu_20221201_036T9

V_BP-kathmandu_20221201_036T9

Date of collection Dec. 1, 2022

Province Bagmati Pradesh

District Kathmandu

Municipality/GaunPalika Kathmandu

Ward 13

Locality Kalimati tarkari bazaar

Vegetable Name Carrot

Vegetable Origin kaalimati bazaar

Latitude 27.698000

Longitude 85.299000

Site Image 



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प्रदेश सरकार
सामाजिक विकास मन्त्रालय
प्रदेश जनस्वास्थ्य प्रयोगशाला
मधेश एरिया, जनकपुरधाम

Lacuna
Fund

Parasitoscope NAAMI

Water / W_P1-dharan_20230224_8YVDZ / 3 / brightfield

Brightfield

Slide 3 for W_P1-dharan_20230224_8YVDZ



W_P1-dharan_20230224_8YVDZ_S3_11_B 18722
Not Approved




W_P1-dharan_20230224_8YVDZ_S3_12_B 18724
Not Approved

Parasitoscope NAAMI

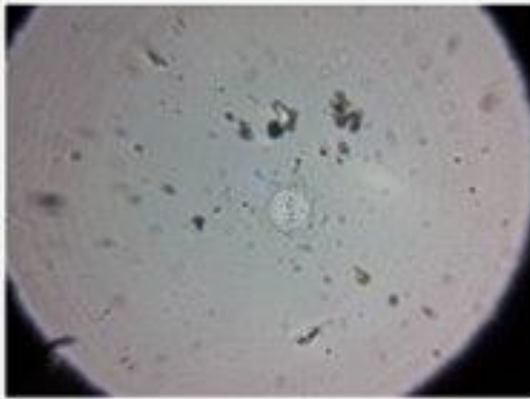
Vegetable / V_SP-mangalsen_20221204_VQWQJ / 1 / smartphone

Smartphone

Slide 1 for V_SP-mangalsen_20221204_VQWQJ



V_SP-mangalsen_20221204_VQWQJ_S1_11_5 11915
Not Approved

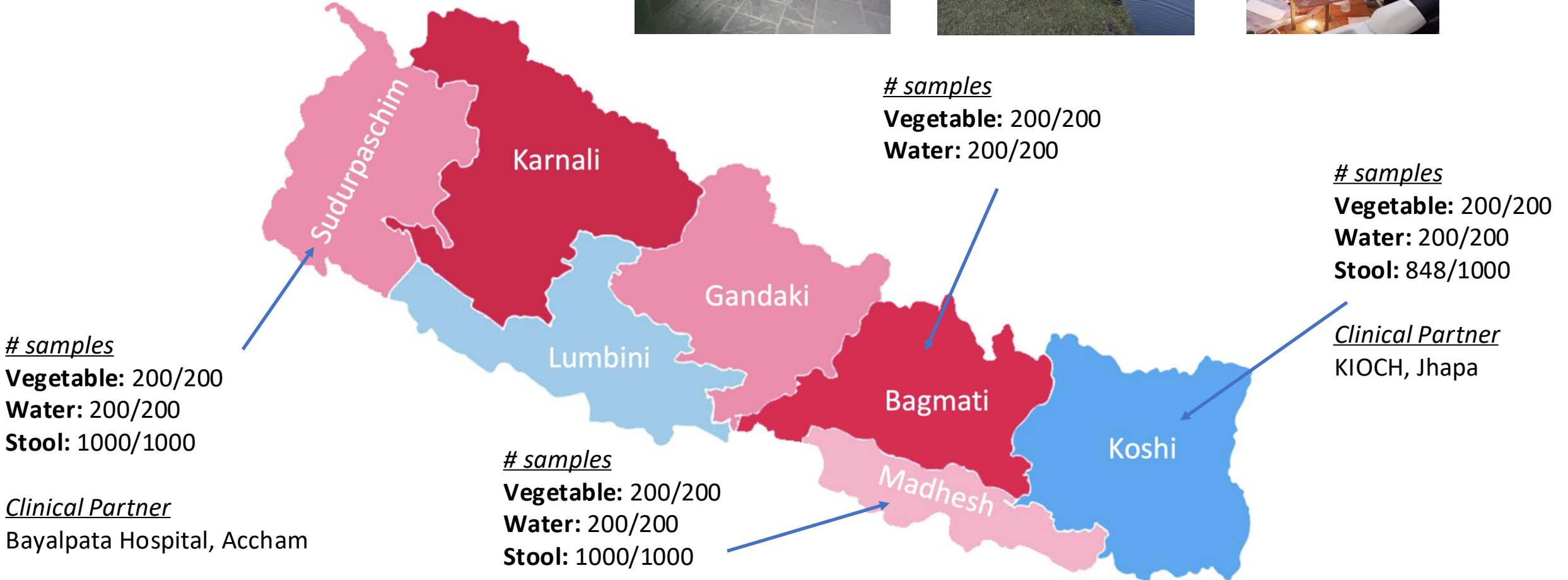


V_SP-mangalsen_20221204_VQWQJ_S1_12_5 11915
Not Approved

Sample Collection Stats

smartphone images uploaded: **194,775**

brightfield images uploaded: **193,020**



Resource-Constrained Settings in Healthcare

Lack of experts

- Lack of medical doctors, radiologists in primary and community health care settings

Lack of devices, algorithms, or technologies

- CT Scans and MRIs are expensive; more advanced expensive not available
- AI: Lack of Data/Internet/compute resources/financial resource

Lack of research and innovation

- Neglected Diseases
- Inability to solve problems quickly: Dengue is killing more & more people in Kathmandu
- Emerging useful technology being inaccessible (e.g. chatbot due to language barrier)

Resource-Constrained Settings: Data Scarcity

Weakly Supervised

- [Weakly supervised localisation for fetal ultrasound images](#) 22 2018
N Toussaint, B Khanal, M Sinclair, A Gomez, E Skelton, J Matthew, ...
Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical ...

Semi-Supervised, Unsupervised learning

- [Fixmatchseg: Fixing fixmatch for semi-supervised semantic segmentation](#) 14 2022
P Upretee, B Khanal
arXiv preprint arXiv:2208.00400

Synthetic Data

- [Synthetic boost: Leveraging synthetic data for enhanced vision-language segmentation in echocardiography](#) 6 2023
R Adhikari, M Dhakal, S Thapaliya, K Poudel, P Bhandari, B Khanal
International Workshop on Advances in Simplifying Medical Ultrasound, 89-99

Resource-Constrained Settings: Low Compute

Minimal to no Finetuning in VLMs an Foundation Models

MICCAI Brats Workshop 2024

- Parameter-efficient Fine-tuning for improved Convolutional Baseline for Brain Tumor Segmentation in Sub-Saharan Africa Adult Glioma Dataset** 2024
B Adhikari, P Kulung, J Bohaju, LK Poudel, C Raymond, D Zhang, ...
arXiv preprint arXiv:2412.14100

MICCAI 2024

- Vlsm-adapter: Finetuning vision-language segmentation efficiently with lightweight blocks** 1 2024
M Dhakal, R Adhikari, S Thapaliya, B Khanal
International Conference on Medical Image Computing and Computer-Assisted ...

ACCV 2024

Rabin Adhikari, Safal Thapaliya, Manish Dhakal, Bishesh Khanal:

TuneVLSeg: Prompt Tuning Benchmark for Vision-Language Segmentation Models. ACCV (3) 2024: 44-62

Resource-Constrained Settings in Healthcare

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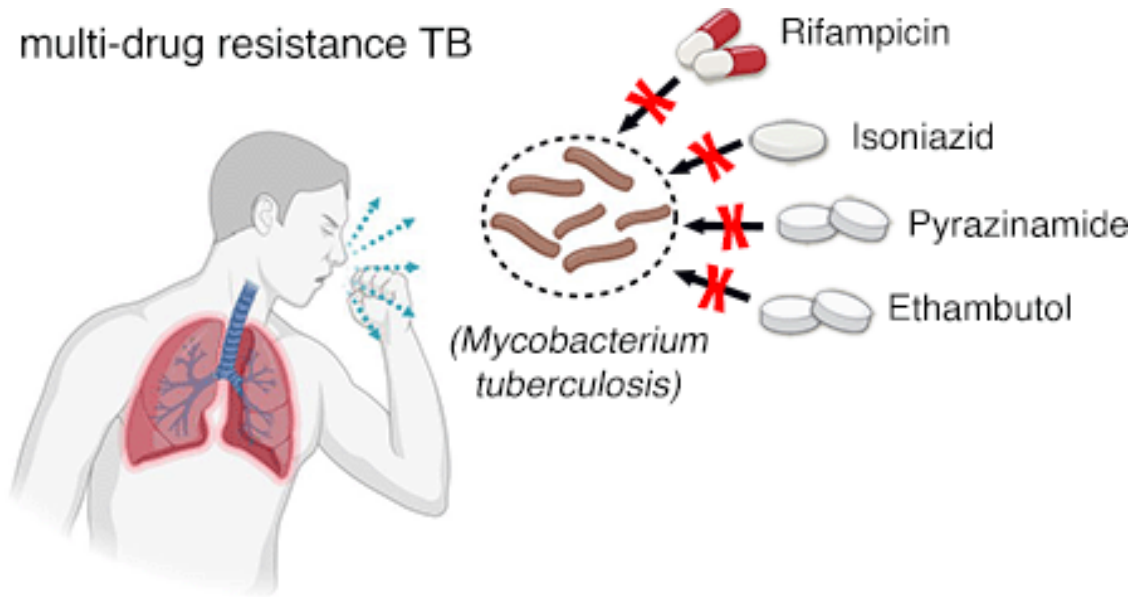
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Lack of research and innovation

- Neglected Diseases
- Inability to solve problems quickly: Dengue is killing more & more people in Kathmandu
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Tuberculosis: Still not a solved problem!



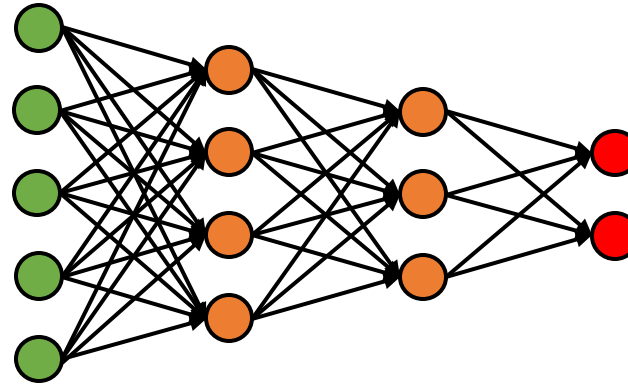
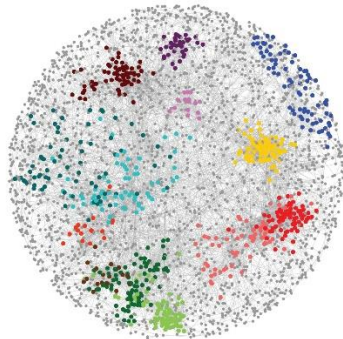
Lead: Dr. Raunak Shrestha
Computational Genomics
Group @NAAMII

- Nepal has high TB burden
- TB bacteria are spread from person to person through the air
- Multi-drug resistant TB is biggest bottleneck in its eradication
- Gene mutations leading to multi-drug resistant TB are largely unknown

Predicting Multi-drug Resistant TB from Whole Genome Sequence

TB mutations

```
ACCTGCTACACGC GGCAGGCAACTATGCCCAACGG  
ATGACAGGACTGCTGGACGGCAAACGGATTCTG  
GTTAGCGGAATCATCACCGACTCGTCGATCGCGTTTC  
GGAGGTTCATCGTCGGCATGGACTTCGACCCGAGCCGGGCGAT  
GTTAGCGGAATCATCACCGACTCGTCGATCGCGTTTC
```



Predicting drug-resistant TB
and drug-resistant mutations

Protein-Interaction Network



Lead: Dr. Raunak Shrestha
Computational Genomics
Group @NAAMII

(work under progress)

Resource-Constrained Settings in Healthcare

Lack of experts

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- AI: Lack of Data/Internet/compute resources/financial resource

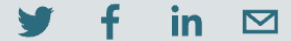
Lack of research and innovation

- Neglected Diseases
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- Emerging useful technology being inaccessible (e.g. chatbot due to language barrier)



Evaluating Nepali Sexual, Reproductive and Maternal Health Chatbot with Large Language Models (LLMs)

SHARE THIS



INITIATIVE

Grand Challenges

CHALLENGE

Artificial Intelligence

FUNDING DATE

Jul 9, 2023

PRINCIPAL INVESTIGATOR

Bishesh Khanal

ORGANIZATION

Nepal Applied Mathematics and Informatics Institute for Research

Bishesh Khanal of the Nepal Applied Mathematics and Informatics Institute for Research in Nepal will assess LLMs for their ability to provide accurate information on sexual, reproductive, and maternal health (SRMH) topics in Nepali to the general public and female community health volunteers. In Nepal, limited access to



LLMs: Evaluating Nepali Sexual, Reproductive & Maternal Health Chatbot With Large Language Model



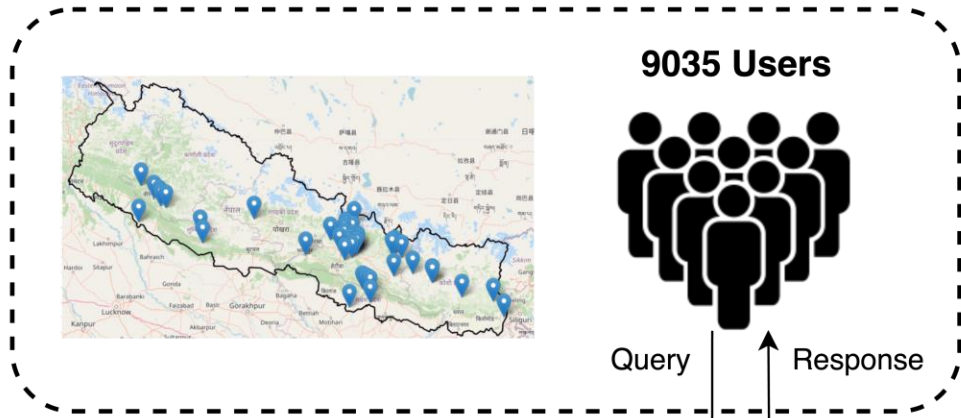
DIYO.AI
LOCALIZING AI



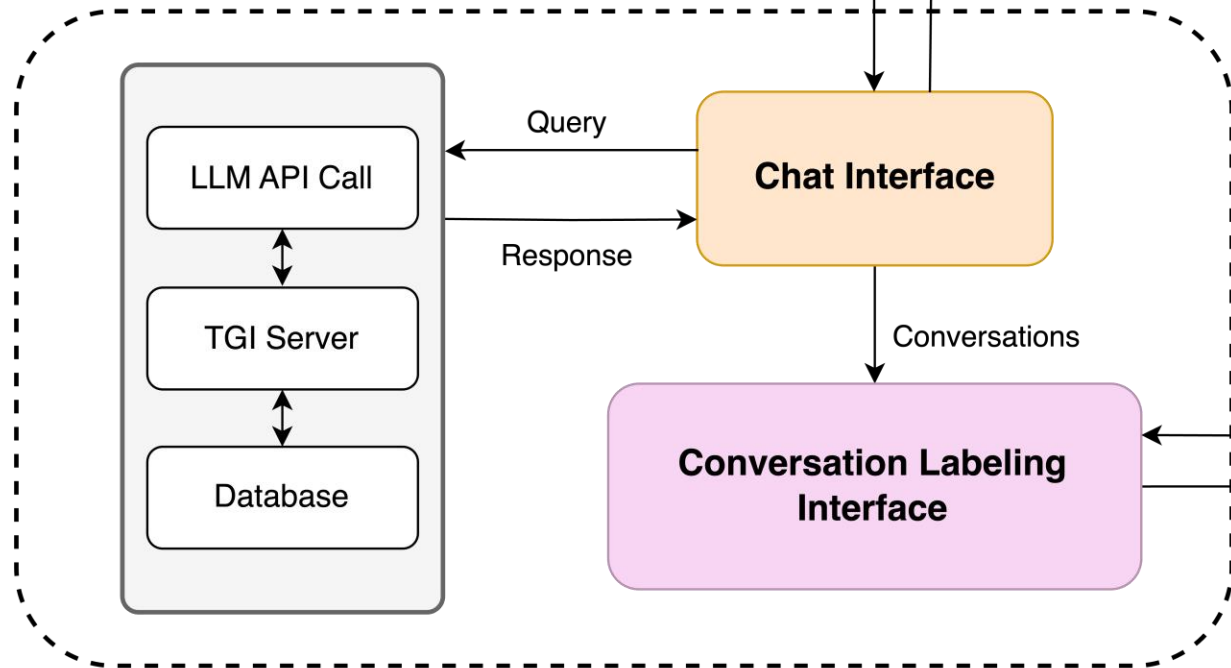
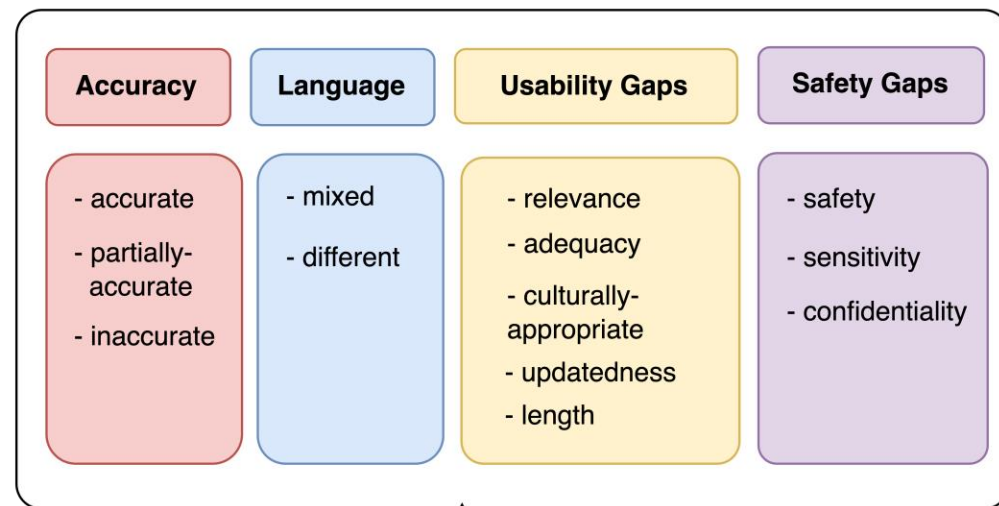
Sharma, M., ..., & **Bishesh Khanal**. Evaluating Large Language Models' Responses to Sexual and Reproductive Health Queries in Nepali. *Under Review at Scientific Reports*

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Data Collection



LEAF Framework

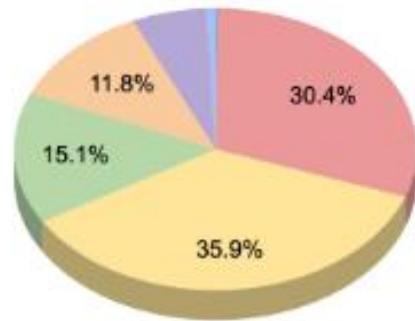


Conversation Handling Platform

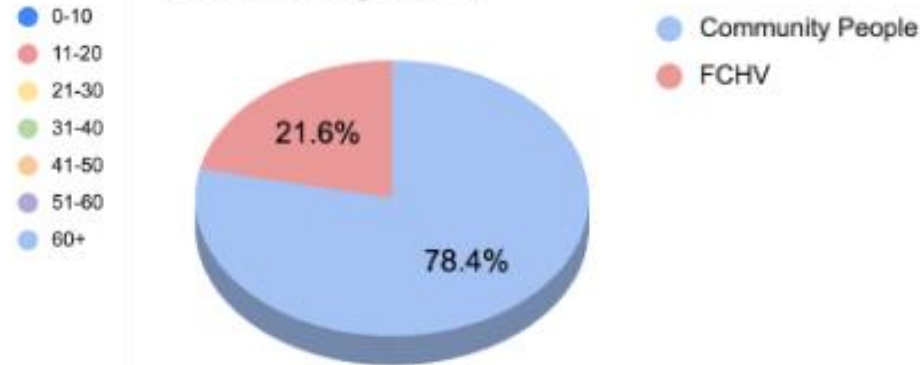


Dataset

Age Distribution



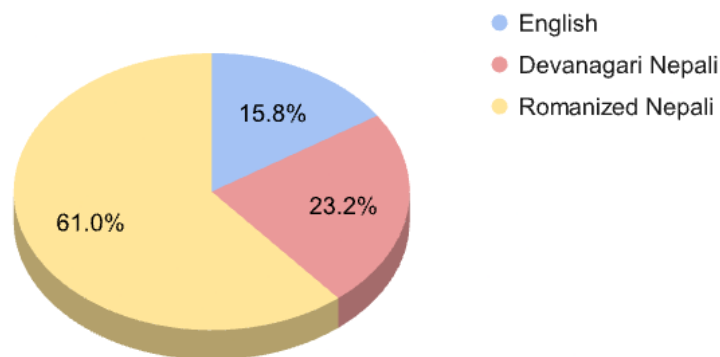
User Background



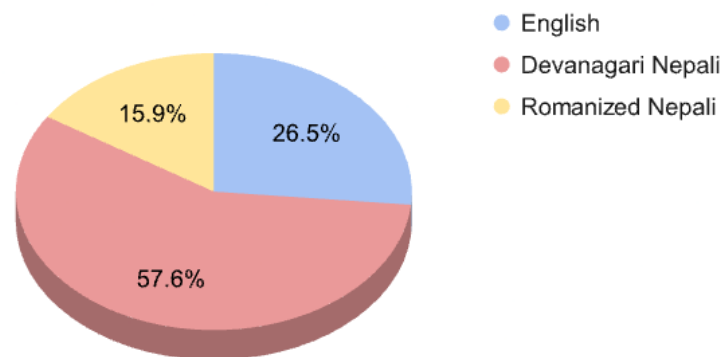
Location	Count	Percentage(%)
Bagmati Province	3458	38.27
Gandaki Province	685	7.58
Karnali Province	670	7.42
Koshi Province	1487	16.46
Lumbini Province	940	10.40
Madhesh Province	1088	12.04
Sudurpaschim Province	707	7.83

Dataset

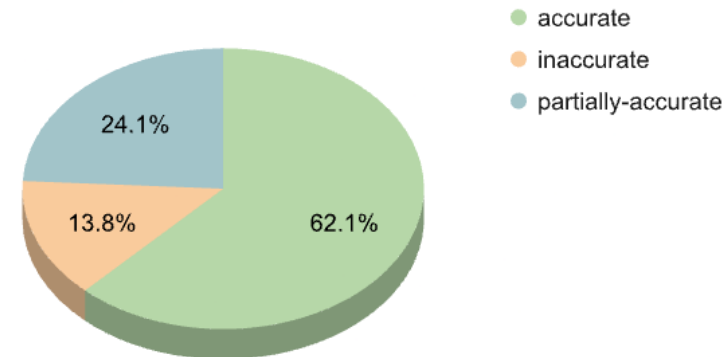
User Query Language



Bot Response Language



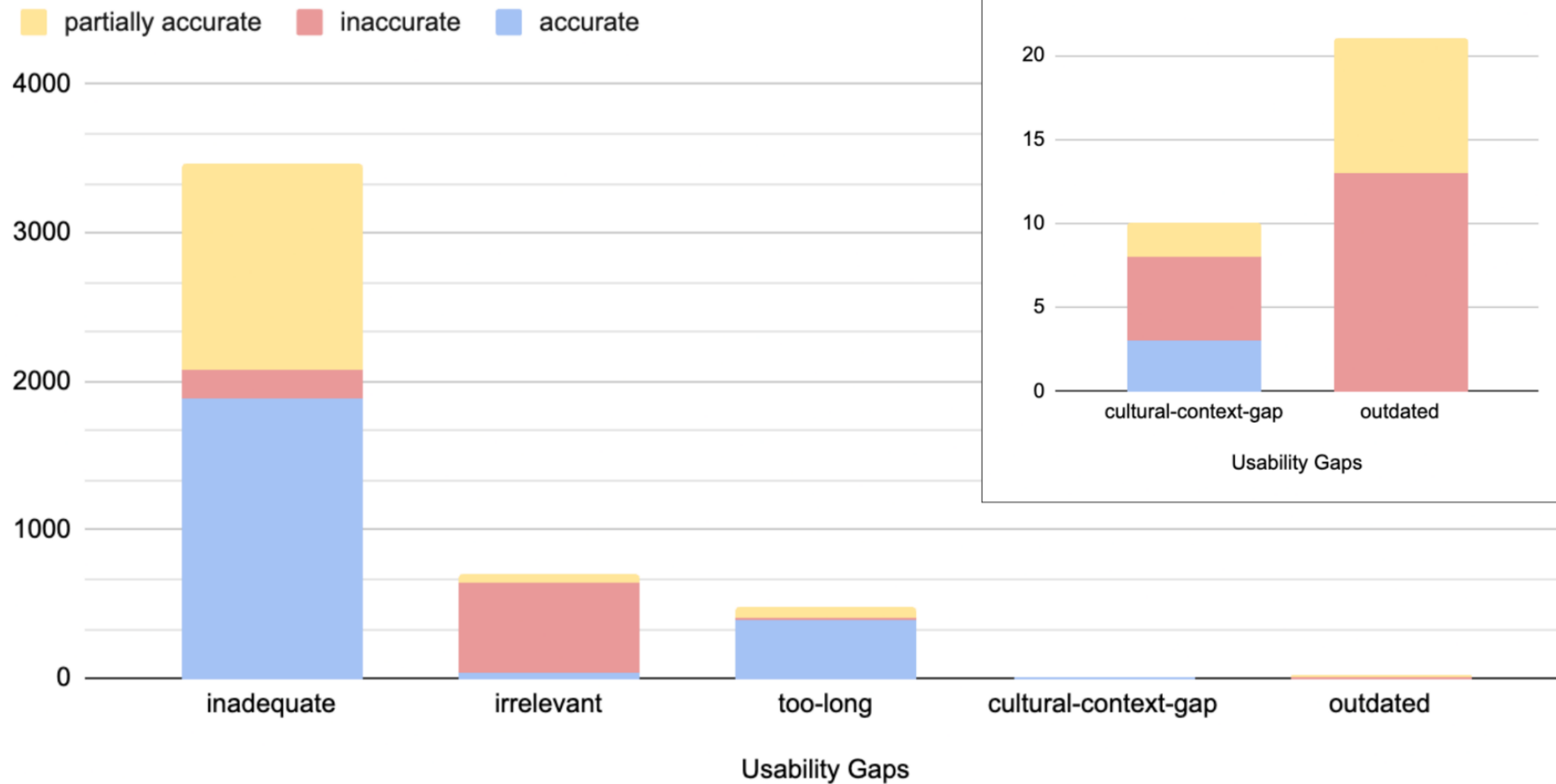
Accuracy



Safety Gap	Count	Percentage of Total Responses(%)
unsafe	98	0.74
insensitive/offensive	51	0.38
non-confidential	7	0.05

Dataset

Usability Gaps across all Responses



Outline

Resource-Constrained Settings in Healthcare

Health AI in Resource-Constrained Settings with Examples from Nepal

Trustworthy AI in Healthcare

Trustworthy AI in Healthcare

Risks due to things going wrong very high

Stronger regulatory frameworks for deployment approval

Clinical translation of research and products: What's for AI compared to clinical trials?

Implementation Science & Public Health: Looking into Health Systems and Socio-Economics



FUTURE-AI: Best practices for trustworthy AI in medicine

FUTURE-AI is an international, multi-stakeholder initiative for defining and maintaining concrete guidelines that will facilitate the design, development, validation and deployment of trustworthy AI solutions in medicine and healthcare based on six guiding principles: Fairness, Universality, Traceability, Usability, Robustness and Explainability.

1

FAIRNESS

The Fairness principle states that medical AI tools should maintain the same performance across individuals and groups of indiv...

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2

UNIVERSALITY

The Universality principle states that a medical AI tool should be generalisable outside the controlled environment where it wa...

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3

TRACEABILITY

The Traceability principle states that medical AI tools should be developed together with mechanisms for documenting and monito...

[Learn More >](#)

4

USABILITY

The Usability principle states that the end-users should be able to use a medical AI tool to achieve a clinical goal efficientl...

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5

ROBUSTNESS

The Robustness principle refers to the ability of a medical AI tool to maintain its performance and accuracy under expected or ...

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6

EXPLAINABILITY

The Explainability principle states that medical AI tools should provide clinically meaningful information about the logic behi...

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Guidelines for AI deployment in healthcare: Large collaborative



FUTURE-AI: International consensus guideline for trustworthy and deployable artificial intelligence in healthcare. Karim Lekadir et al. BMJ 2025.

Trustworthy AI: Human in the Loop and Language Inputs

Radiologists, Surgeons

- Most often the images are seen by medical professionals
- Medical Image Segmentation: a tedious time-consuming task
 - How about **language prompts** to interactively speed up segmentations while being inherently more interpretable?

Trustworthy AI: Human in the Loop and Language Inputs

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Vision Language Models

- [Exploring transfer learning in medical image segmentation using vision-language models](#) 13 2024
K Poudel, M Dhakal, P Bhandari, R Adhikari, S Thapaliya, B Khanal
MIDL, Paris, France 2024 (Medical Imaging with Deep Learning), arXiv ...

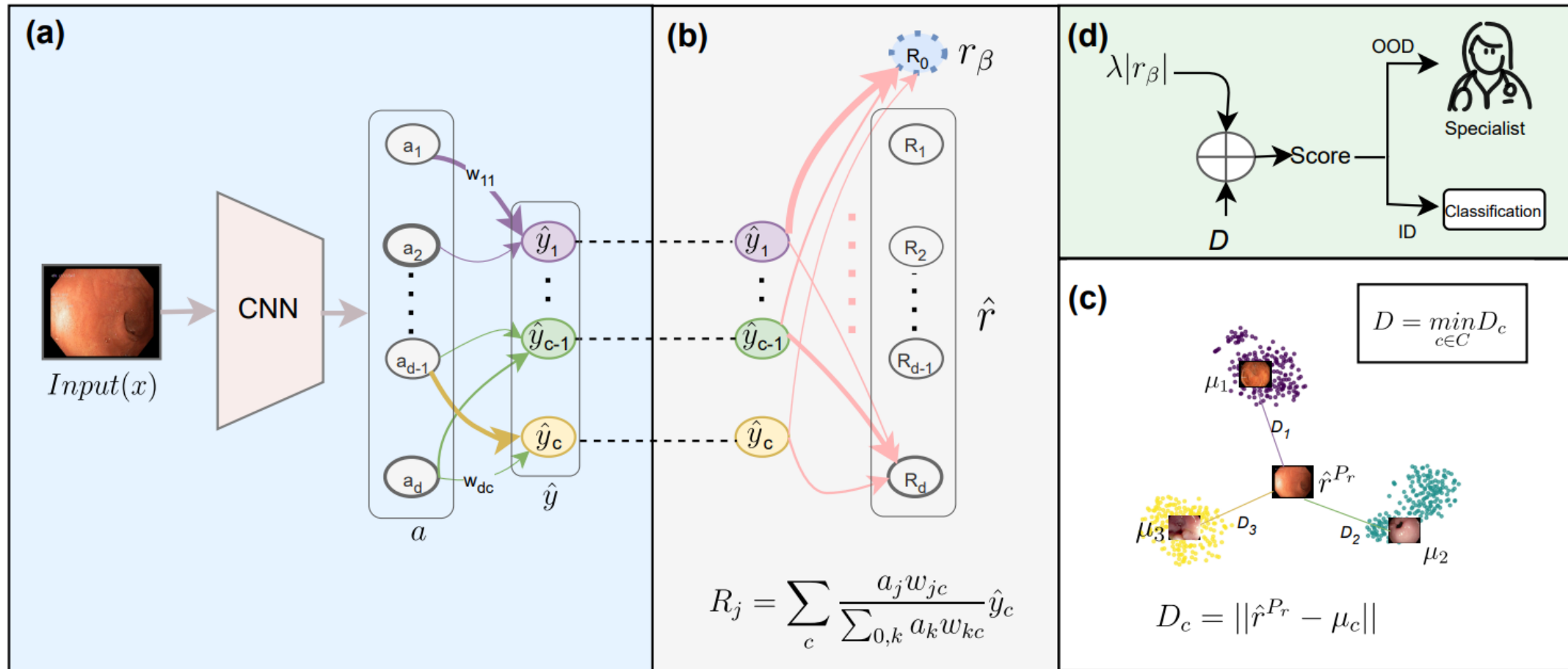
Trustworthy AI: Explainability

Trustworthy AI: Explainability

NERO: Explainable Out-of-Distribution Detection with Neuron-level Relevance

Authors Anju Chhetri, Jari Korhonen, Prashna Gyawali, Binod Bhattarai

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Binod Bhattarai
Lab @
NAAMII

Trustworthy AI: Federated Learning

Med-MMFL: A Multimodal Federated Learning Benchmark in Healthcare

Authors Aavash Chhetri, Bibek Niroula, Pratik Shrestha, Yash Raj Shrestha, Lesley A Anderson, Prashnna K Gyawali, Loris Bazzani, Binod Bhattarai



Binod Bhattarai
Lab @



Medical Multimodal Datasets

BraTS

Symile-MIMIC

Glucose: ...
Magnesium: ...
Labs

PathVQA

Question: ...
Answer: ...

MIMIC-CXR-JPG

Examination: ...
Indication: ...
Radiology Report

EHRXQA

Admissions: ...
LabEvents: ...
EHR as Text

Question: ...
Answer: ...

Data Partition

Natural

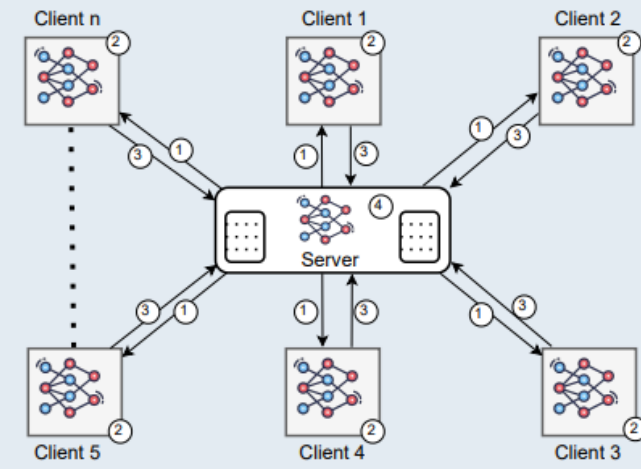


Synthetic



Federated Learning (FL)

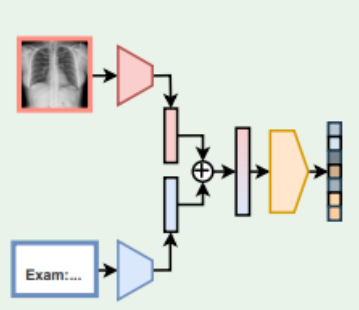
- 1 Server sends global model/representation to clients
- 2 Client Updates local model using Clients' Private Data
- 3 Client sends local model/representation to server
- 4 Server Updates global model by aggregating client updates



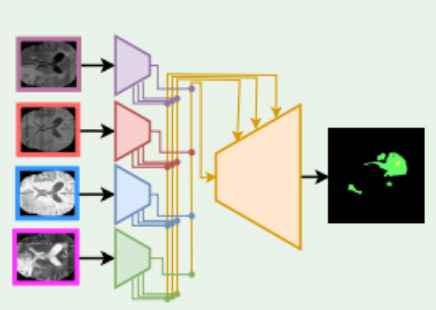
- FL Algorithms**
1. FedAvg
 2. FedProx
 3. SCAFFOLD
 4. MOON
 5. FedNova
 6. CreamFL

Tasks

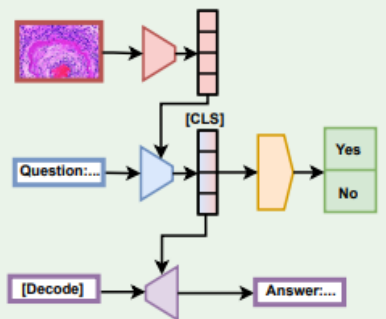
Classification



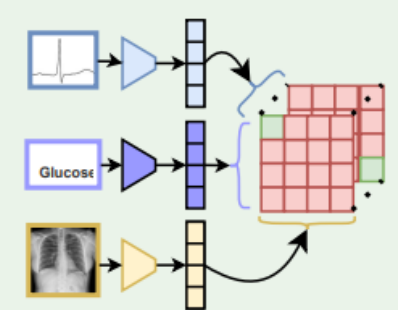
Segmentation



Visual Question Answering



Modality Alignment Pretraining



<https://naamii.org>

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