# Building Socially Impactful Solutions using AI

Public Health & Agriculture

Jigar Doshi - June 2025

#### **ML** Journey

- Georgia Tech Atlanta
- IBM Research New York
- CrowdAI San Francisco
- Wadhwani AI Mumbai
- Artpark, IISC Bangalore

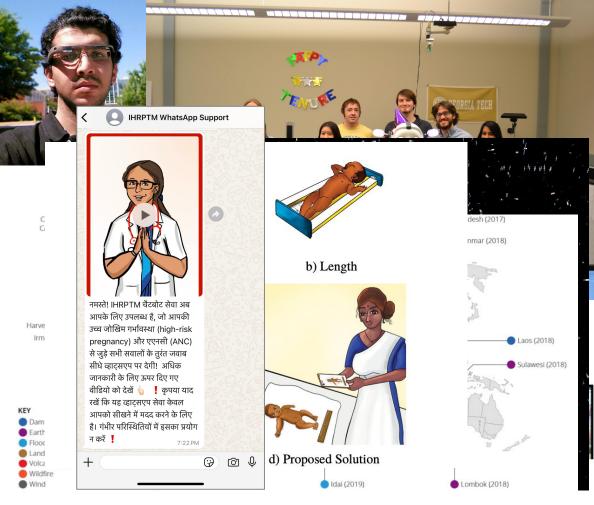


Figure 2: Disaster types and disasters represented in xBD over the world.

### Talk Outline

- Day 1
  - LLMs for Mothers and Frontline health workers
  - TB & Covid Screening using Cough samples
  - AI Solutioning
- Day 2
  - Pest Management
  - Farmer Chat / Remote Sensing
  - AI Agents for Public Health
  - How to pick a problem
    - To build an impactful fulfilling ML career





#### LLM Copilot for Front Line Workers for High-Risk Pregnancy Management May 2024

#### Poor Maternal and Child Health in India

A woman dies in childbirth every 20 minutes; for every woman who dies, 20 more suffer lifelong ailments.

2 children under 5 die every minute; 4 of 10 children don't realize their full potential due to chronic undernutrition/stunting.

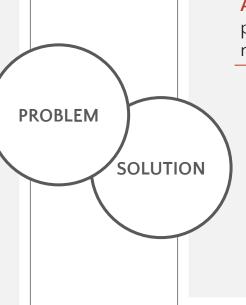
Factors influencing this include:



Lack of access to preventive care information and services, leading to poor understanding of danger signs and delayed care seeking

Real Providence of the second second

Inadequately trained & supported health workers who are unable to detect and manage high-risk conditions in time



**ARMMAN** leverages deep mobile penetration with existing health worker network and infrastructure to:



Provide **preventive care information** through pregnancy & infancy enabling women to seek care in time



Train and support health workers for timely detection & management of high-risk conditions







#### HEALTH WORKERS AND SYSTEMS



#### **mMit**ra

Free voice-call service providing critical preventive care information during pregnancy and infancy



Mobile-based refresher training course for frontline health workers (ASHAs) in partnership with Ministry of Health and Family Welfare



Largest mobile-based maternal messaging programme in the world in collaboration with MOHFW



Live telephonic counselling for caregivers of moderately underweight infants to prevent their decline into severe malnutrition

#### 60 MILLION+

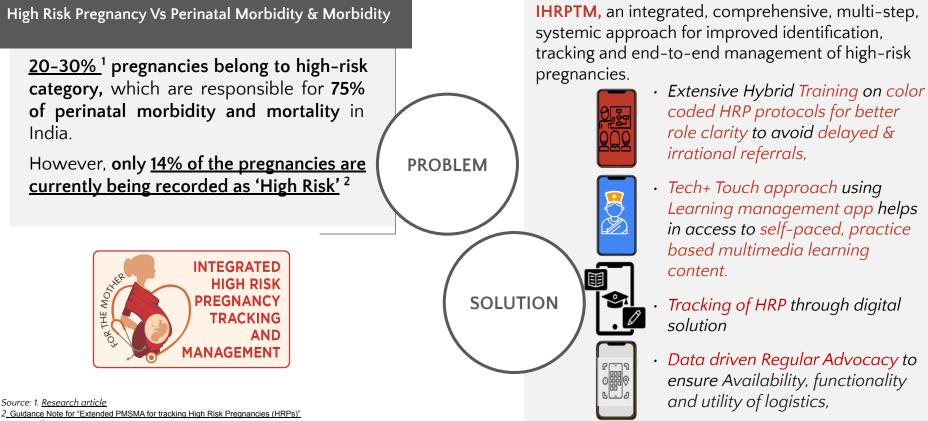
WOMEN AND CHILDREN



Implementation of high-risk management protocols for sustained reduction in delayed referrals and high-risk referrals to tertiary facilities

500,000+ HEALTH WORKERS

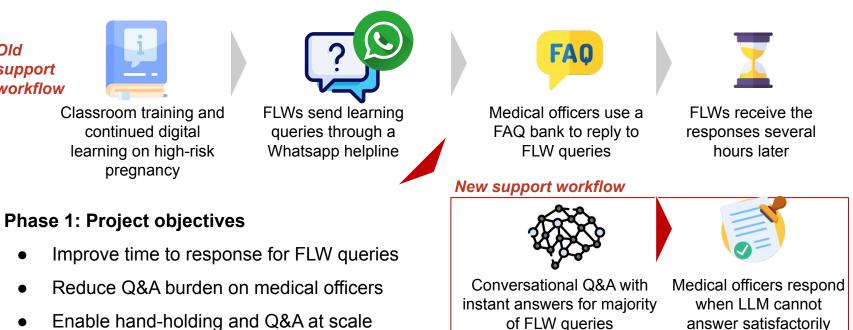
#### ARMMAN's Integrated High Risk Pregnancy Tracking and Management (IHRPTM) program trains and supports 20,000+ health workers across 3 states to detect and manage high-risk pregnancies.



3. SRS Bulletin

# **Chatbot project introduction**

ARMMAN and ARTPARK are building a learning copilot in the IHRPTM digital learning system, starting with automated ANM support for learning queries

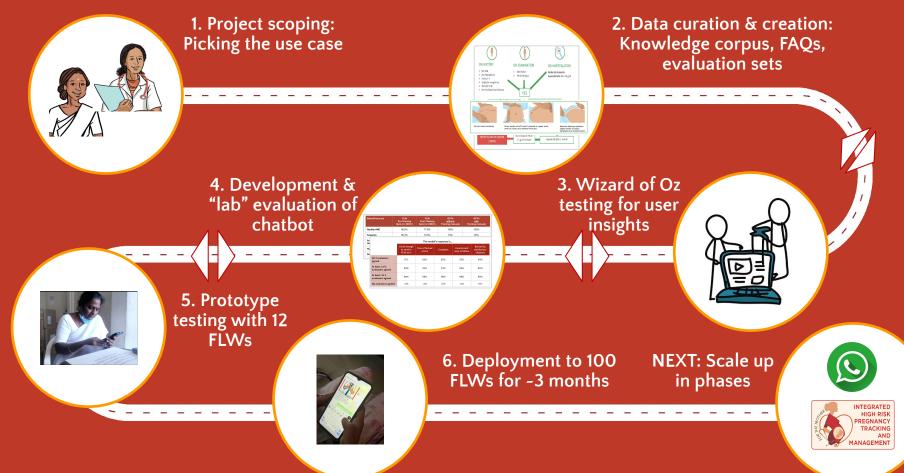


Classroom training and continued digital learning on high-risk pregnancy

Old

support workflow

# Project Journey: Iterative, human-centered approach



# User insights through Wizard of Oz experiments

We conducted 'Wizard of Oz' experiments to understand how an LLM bot will be used, perceived and interpreted by ANMs

#### **Overall**

Good offternoon sir

normal eatha

RBS level normal da entaha undali

Grb test Normal chapader ANC RBS 152

Madam, ఒక Anc కి sugar లెవెల్స్ normal ఎంత ఉంటాయో చెప్పగలరు మేడం

Mild Amime Hb eatha 11:36 am

Anc 16 weeks HB 10g తనకు ఏమి ఇవ్వాలి

ఏమి చేయాలి టాబ్లెట్స్ ఇవ్వాలి 🔢 💷

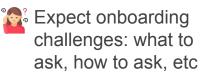
Good afternoon madam

chevali madam

హెచ్ డి పెరగాలంటే మేడం

Anc 2nd trimester lo undi , HB levels 10 grams undi, ela treatment

- For greater adoption, the intro to the bot must be facilitated by a medical officer
- ANMs tend to interact with the platform respectfully ("OK Sir", "OK Madam") as they believe it to involve a credible authority figure



#### Queries

- Queries likely to be phrased as search strings, with complex queries split into multiple messages
- Mix of English and Telugu phrases and fonts used, spelling mistakes common
  - More detail in voice notes vs text queries. Large variations in dialect & pronunciation

#### Responses

**()** 

- Preference for Telugu responses, with medical terminology in English
- Quick response important; delays may trigger other medium of doubt clarification
- Crisp language preferred. Utilize action-oriented verbs, replicating real communication

#### Phase-wise model evaluation strategy

Phase	Evaluations	Objective	Work done
I. Objective evaluation	<ul> <li>ANM pre/post quiz (75 questions, English)</li> <li>FAQ match (-98 questions x 5 variations, English)</li> </ul>	<ul> <li>Validate "domain knowledge" of model</li> </ul>	<ul> <li>Making program content machine-readable / RAG-friendly</li> <li>FAQ match</li> </ul>
II. Human evaluation by experts (Indic Languages)	<ul> <li>Evaluation of generated answers by clinical experts (55 questions x 3 MTOs, English, text) (15 questions x 3 MTOs, Telugu, text) (65 questions x 3 MTOs, Hindi, text)</li> </ul>	<ul> <li>Measure correctness, completeness and conciseness of answers generated by model</li> <li>Measure model performance in Telugu &amp; Hindi</li> </ul>	<ul> <li>Generation of answers, with citations</li> <li>Multilingual support (English, Telugu, Hindi)</li> <li>Tuning answers to be more "user-friendly"</li> </ul>
III. Human evaluation by end users (Indic Languages)	• Field testing of Whatsapp chatbot by ANMs (4 scenarios x 2 modes x 12 ANMs, Telugu, speech & text)	<ul> <li>Understand user acceptability of responses</li> <li>Predict likely failure points at deployment</li> </ul>	<ul> <li>Multimodal support (text and voice)</li> <li>WhatsApp integration</li> </ul>
IV. Pilot + deployment	<ul> <li>Limited deployment with 1000 ANMs</li> </ul>	<ul> <li>Understand usability, correctness, usefulness of chatbot</li> </ul>	<ul> <li>Integration with WhatsApp helpline</li> <li>Human in the loop</li> </ul>

### **I. Model performance on FLW quiz**

Risks/Protocols	FLW Pre-Training Quiz (n= 6000+)	FLW Post-Training Quiz (n= 6000+)	GPT4 <u>without</u> Training manuals	GPT4 <u>with</u> Training manuals
Quality ANC	66.6%	77.8%	100%	100%
Anaemia	66.3%	74.6%	73%	93%
Antepartum Hemorrhage (APH)	67.2%	79%	80%	100%
Hypertension	65.9%	75.6%	93%	93%
Gestational Diabetes	46.8%	63.3%	73%	100%

#### I. Model performance on FAQ match

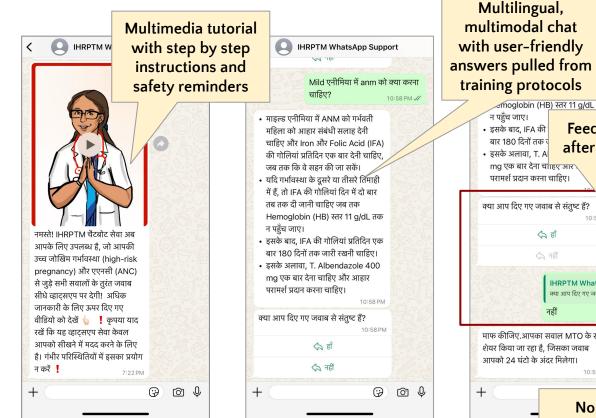
Evaluation	No. of questions	Mean accuracy	Standard deviation of accuracy
FAQ Set (Exact)	80	100%	-
FAQ Set (Paraphrased, 5-fold)	80x5	96%	1.37%
Expert-created question set (Exact)	18	94%	-
Expert-created question set (Paraphrased, 5-fold)	18x5	75%	7.96%

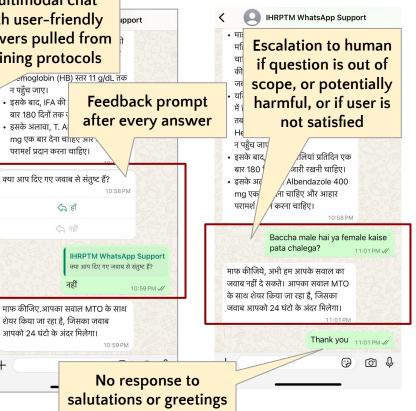
### II. Model performance on expert evaluation

#### The model's response is...

	Good enough to send to FLW as is	Free of factual errors	Complete	Concise and easy to follow	Backed by satisfactory citations
All 3 evaluators agreed	71%	85%	82%	55%	49%
At least 2 of 3 evaluators agreed	84%	93%	93%	69%	80%
At least 1 of 3 evaluators agreed	98%	98%	98%	98%	89%
No evaluators agreed	<2%	<2%	<2%	<2%	11%

# Chatbot overview





#### **Chatbot Demo**

+

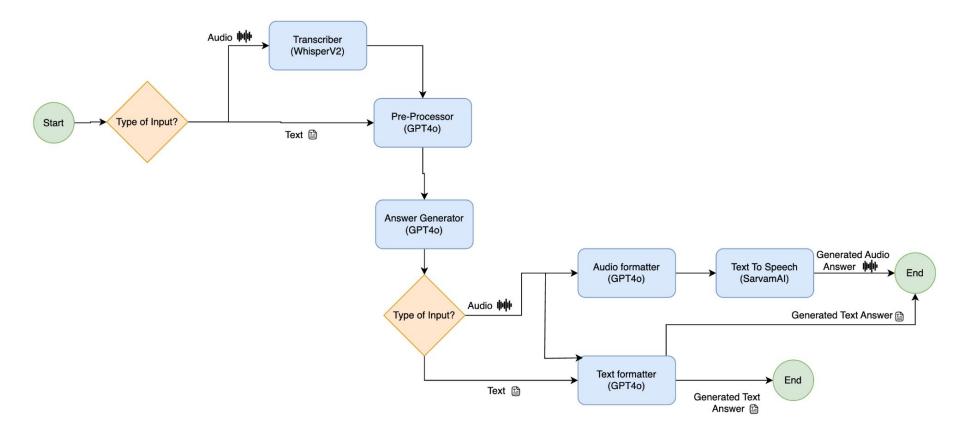
2:11

- IHRPTM WhatsApp Support < 1 पोषक आहार पर जोर दिया जा सके।
  - एक महीने के बाद प्रगति की जांच के लिए एक follow-up Haemoglobin (Hb) test करना चाहिए।
- अगर Haemoglobin (Hb) स्तर में महत्वपूर्ण वृद्धि नहीं होती या कम से कम 1 g/dL तक नहीं बढ़ता, तो रोगी को Medical Officer (MO) या किसी उचित चिकित्सा केंद्र के लिए संदर्भित करना चाहिए।

3:34 PM







# Pilot: A Snapshot (March 2025)

# 100 FLWs enrolled

in stages across 2 districts in Uttar Pradesh

# 600+ queries

received from 72 FLWs

### 91% satisfactory responses

as rated by domain expert

# 92% positive feedback

by users on responses received

#### 80% repeat users

who come back for second session

11% voice queries

vs 89% text queries

43% queries

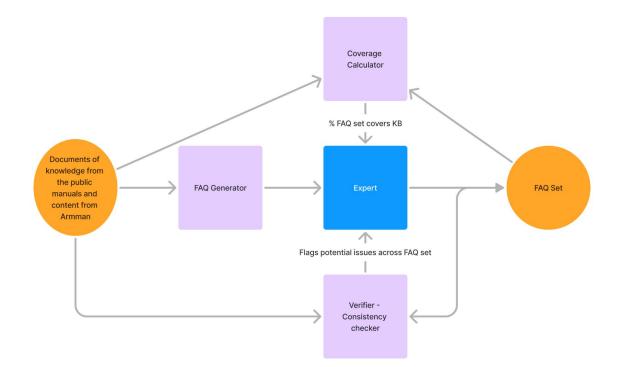
escalated to human in the loop



### LLM assistant's for Mothers

- Kilkari National Program: ~5M Mothers each year
- Current program is canned messages 2 times a week
- Before moving to LLM based conversation, build a verifiable system
- Verifiable: All responses are vetted
- Solution:
  - Offline QA Bank generation + Retrieval System
  - Can be deployed locally. 33M Embedding Model + Similarity Search
  - Cheap and efficient

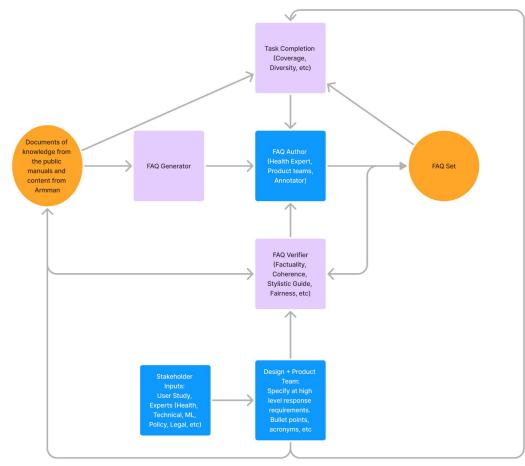
#### LLM + Human Exhaustive QA



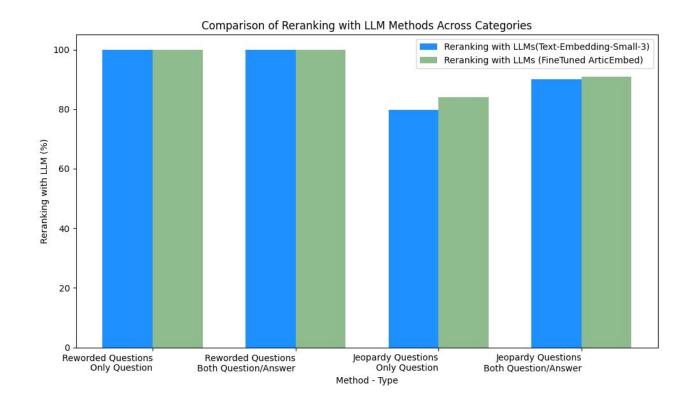
- Hallucination free
- Fast and Offline
- Converts 60K tokens
   knowledge base to 2K
   QA pairs

### LLM + Human Exhaustive QA

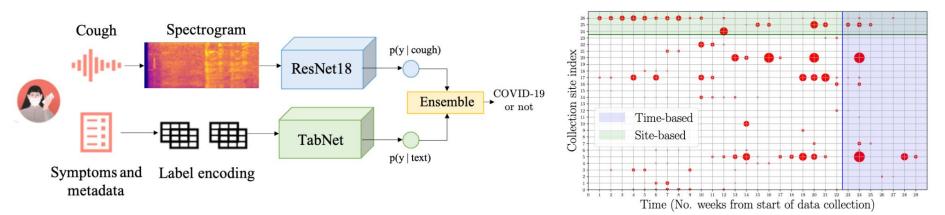
- Hallucination free
- Converts 60K tokens knowledge base to 2K QA pairs
- Product Insights
- LLM Calls
- Knowledge



#### Results – Fine Tuned Embedder (33M)



# Covid Screening using Cough



(a) Schematic diagram of the proposed solution

(b) Data splitting strategy

ICLR 2021 - Workshop <u>Link</u> Main Paper - <u>Arxiv</u>

#### Covid Screening using Cough

Prevalence	Testing Capacity
1%	+44%
5%	+43%
10%	+41%
30%	+33%

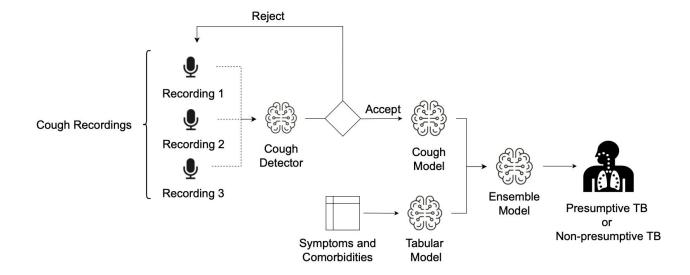
Table 4: *Utility of our triaging tool*. We show the increase in the effective testing capacity of a system at different disease prevalence levels.

## Screening TB based using Cough

Motivation:

- India accounts for ~26 % of global TB cases.
- Symptom-based screening misses partially symptomatic or asymptomatic cases.
- X-ray access is limited in many community settings.
- Need for a low-cost, deployable screening tool superior to symptom screening and more accessible than radiography.

#### Screening TB based using Cough



**Fig. 4** An overview of the AI-based Pulmonary TB screening tool. The tool takes as input three solicited cough sound recordings which are validated using a cough detector and input to the cough TB model to obtain a likelihood score for the presence of TB. The symptoms, their duration, and comorbidities are input to the tabular model which gives another TB likelihood score. These two scores are combined and the resulting output thresholded to determine if the subject has presumptive TB or not.

### Screening TB based using Cough

#### Key Results & Impact

- Test-Set Performance (n = 1 551; TB prevalence = 53 %):
- Sensitivity: 91% Specificity: 69 %

Field Deployment:

- Screened 113063 subjects; flagged 17973 as presumptive TB.
- Of 5584 with diagnostic follow-up:
  - 359 confirmed TB cases (6.4 %), including **50 cases (14 %) missed by**

#### symptom screening.

Implications:

- Detects partially/asymptomatic TB cases, reducing missed diagnoses.
- Scalable for low-resource settings without radiography, augmenting TB control efforts.



#### Early pest warning and advisory system

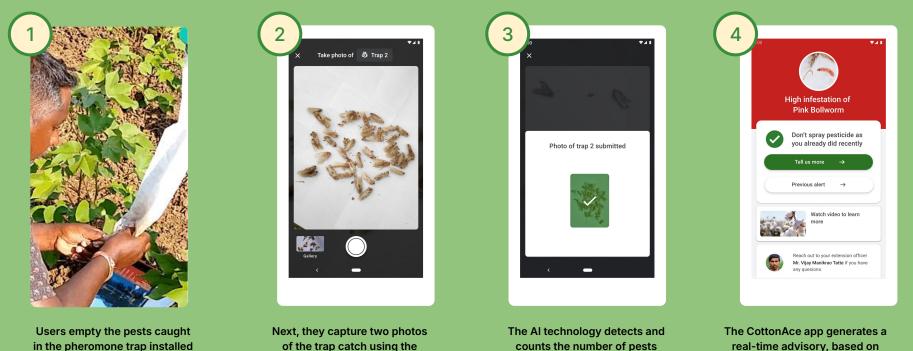
#### CottonAce is an AI-powered early pest warning and instant advisory system developed by Wadhwani AI.

This pest management system helps cotton farmers to protect their crops by determining the right time to spray pesticides through immediate and localized advice, and helps extension program officers and administrators to monitor the solution.



Slides from Jerome White

Early Pest Warning and Advisory System Using computer vision to count and identify pests infecting cotton crops and provide advisory to smallholder farmers.



found in the trap.

scientific action thresholds.

of the trap catch using the

CottonAce app.

in the pheromone trap installed at their farm.

#### Cotton in India...

#### ... is important

- Leads the world in<sup>\*</sup>
  - Production: ~25% of world total  $\cap$
  - Area under cultivation ~41% of world total  $\cap$
- Has an estimate 6 million cotton farmers
  - More than 75% are smallholder
  - And an additional 40-50 million people engaged in related activities

#### Pink bollworm may eat up half of Maharashtra's cotton crop

Warning of unprecedented Maharashtra cuts cotton forecast on November 17, 2017 12:34 am | Updated o worm infestation

Maharashtra has cut its forecast for output of the fibre by 37 percent from its September outlook as a pest infestation has reduced yields.



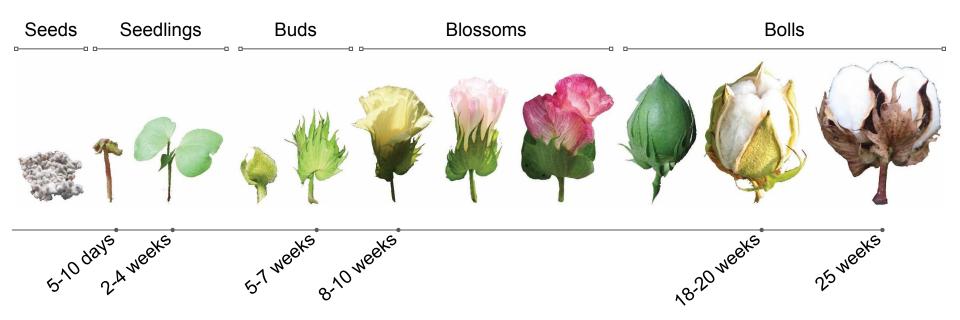
Published: 24th January 2018 04:41 PM | Last Updated: 24th January 2018 04:41 PM

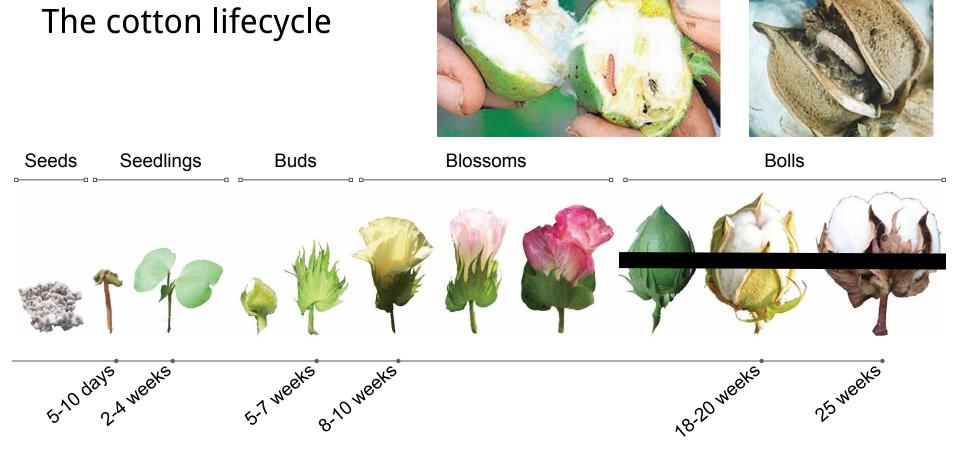
#### ... is not easy

- Pest attacks responsible for ~30% crop yield loss
  - 70% estimated proportion of pest damage caused by hollworms
- Half of India's total pesticide usage is on cotton



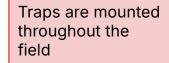
#### The cotton lifecycle





#### Pest traps

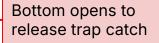
- Traps that can be placed in the field to monitor pest populations
- A recent push by the government to get more farmers using them

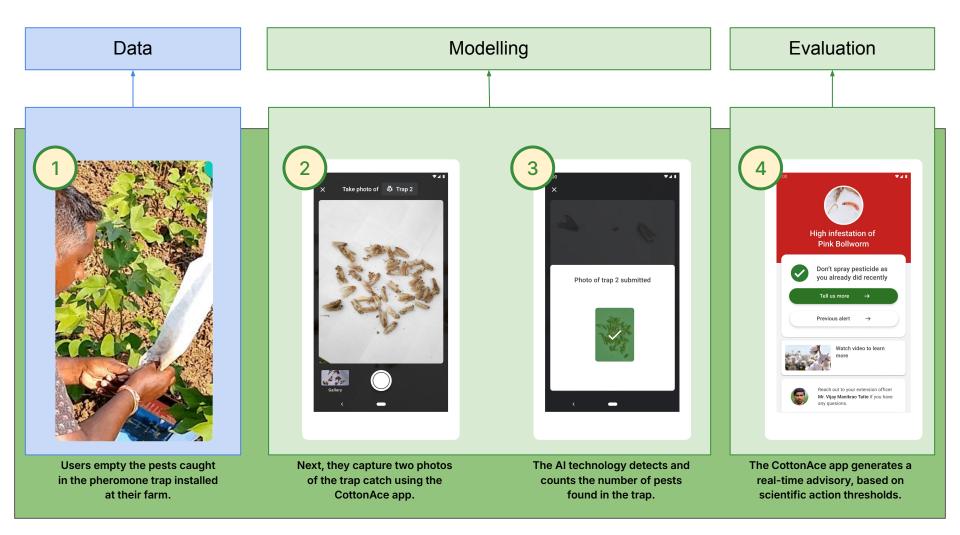




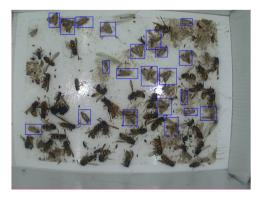


- Lure emits a pheromone that attracts males
- Different lures attract different bollworms



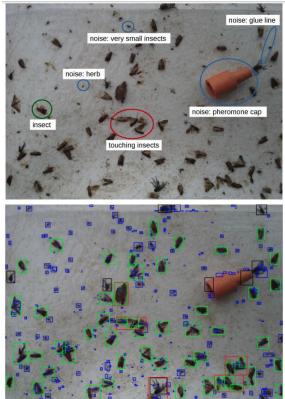


#### Existing datasets





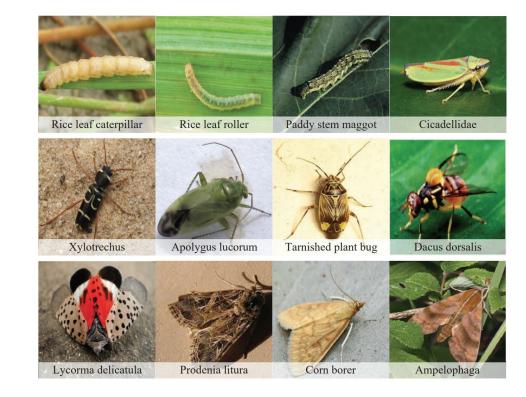
Ding and Taylor, 2016



Bakkay et al., 2018

### IP102 [Wu et al. 2019]

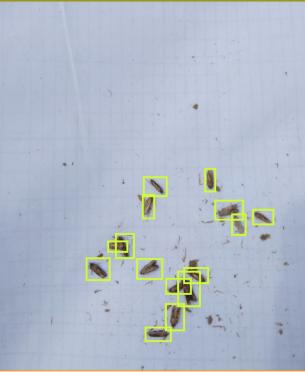
- 75K images across 102 categories
- Images extracted from internet search engine results



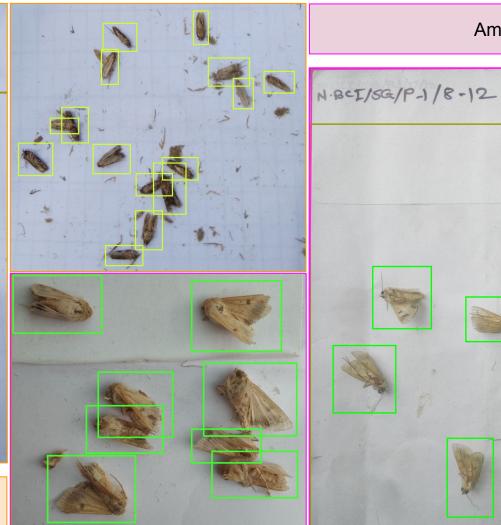
### Data collection: process



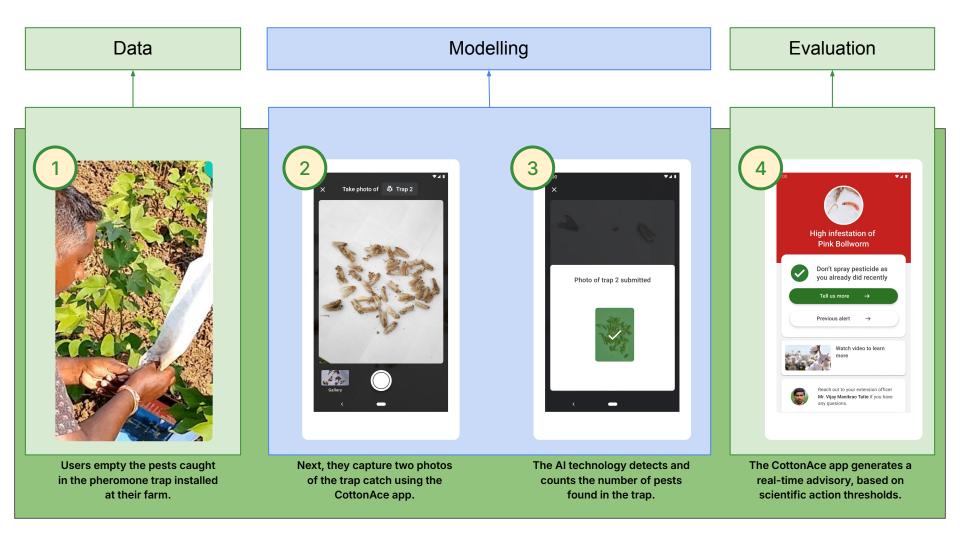
BCI | RV-1 / P.2 JOI-10 INMH 8808017



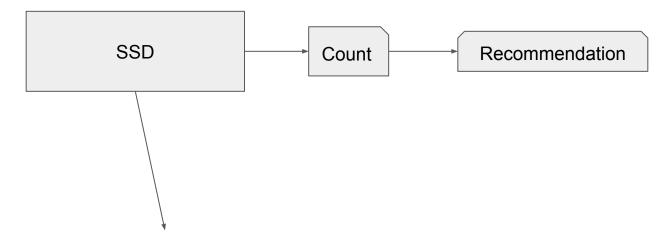
Pink bollworm



#### American bollworm



### System workflow V1 (~2018)

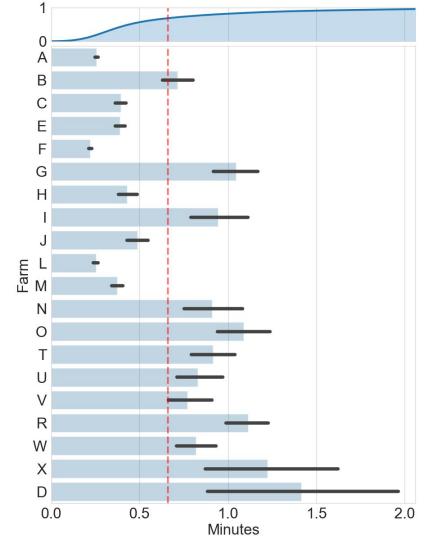


Single Shot MultiBox Detector [Lui et al 2016]

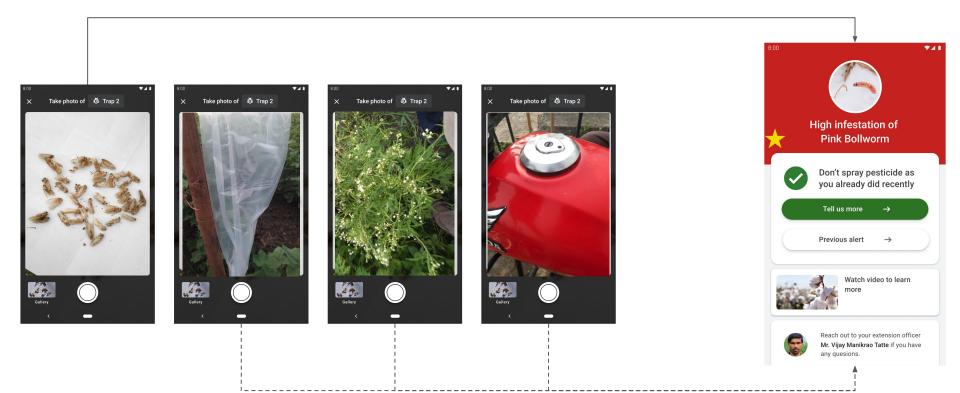
- Seminal architecture in object detection timeline
- Stable, established open source implementation in PyTorch
- Found to perform well on insect detection [Nam and Hung 2018]

### Early lesson: upload time

- Small study in early 2019
- Very early version of Cotton Ace
- Figure: Average upload time per field
- Should not rely on internet!



### Early lesson: interaction varies

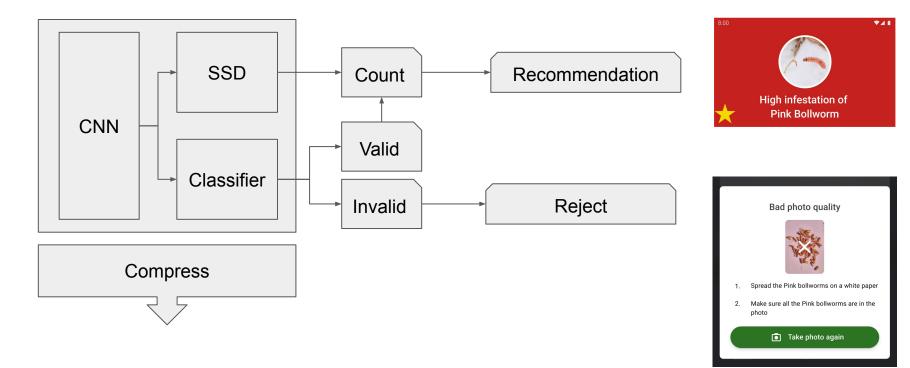


### Scale of the negatives

25K-ODK ends Collected 20K-15K-App begins s 10K-0 Feb '20 Aug '21 Feb '23 Aug '18

Positive images -- Negative images

```
System workflow V2 (~2019)
```



### 2022: A combination of ideas

Our current model (2023) is a result of several ideas coming together

- 1. Alert abstention
- 2. Alert delay
- 3. Model development using the crowd

### **OOD Rejection - Saw Tooth**

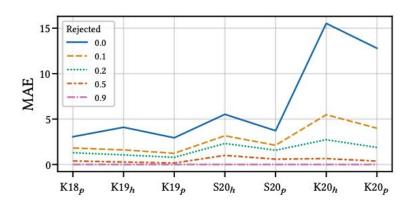


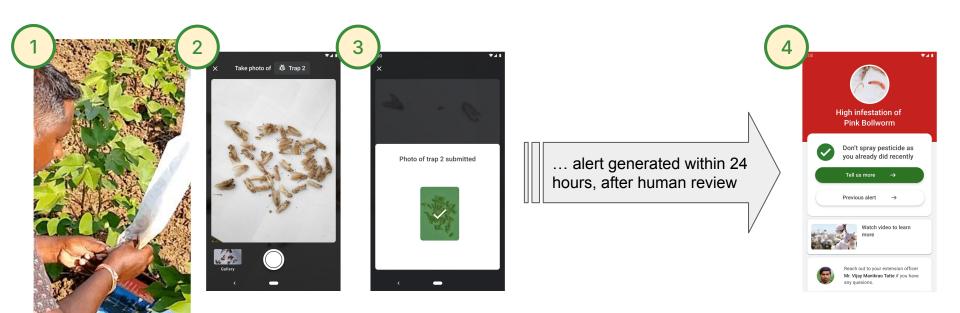
Figure 1: Model performance across seasonal (2018–2020) development and test sets. With each season performance decreases (increasing  $X_p$ 's), but can be improved by training on that seasons data (decrease in immediate  $X_h$ 's). Performance can improve further by rejecting some fraction of worst-performing samples.

	Train	Test
S20 <sub>h</sub>	• Data up to summer 2020 start	Data from summer 2020
S20 <sub>p</sub>	• S20 <sub>h</sub> + data from that season	Data from summer 2020

White, J., Madaan, P., Shenoy, N., Agnihotri, A., Sharma, M., & Doshi, J. (2022). A Case for Rejection in Low Resource ML Deployment. Challenges In Deploying And Monitoring Machine Learning Systems Workshop, NeurIPS 2022

### 2022: A combination of ideas $\rightarrow$ *Alert delay*

- During the 2022 season, a group of users did not receive alerts immediately
- Instead...



### 2022: A combination of ideas $\rightarrow$ Using the crowd



Harvard John A. Paulson School of Engineering and Applied Sciences Wednesdays @ 12:45pm - 3:00pm SEC LL2.223 (Allston Campus)



### Wadhwani AI Bollworm Counting Challenge

FAIR FORWARD

Z ND

WADHWANI AI

Can you improve a pest control app by counting the number of bollworm moths per image?

€15 000 EUR **1**5 000 points



### **Overall** performance

Objective:

- Classify pests in an image and count them
- Correctly provide zero for images with no pests

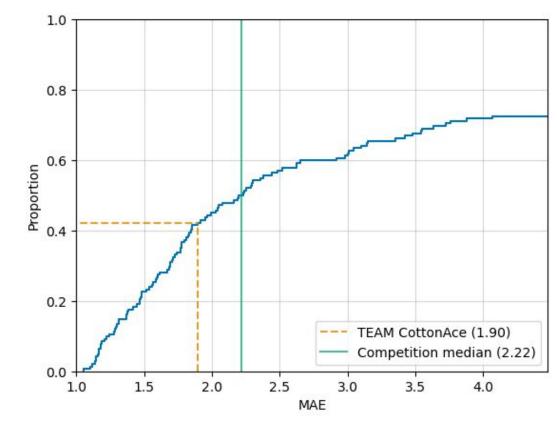
Figure

- Proportion of teams with errors less than a given value
- MAE based on complete (public and private) test set

Takeaways

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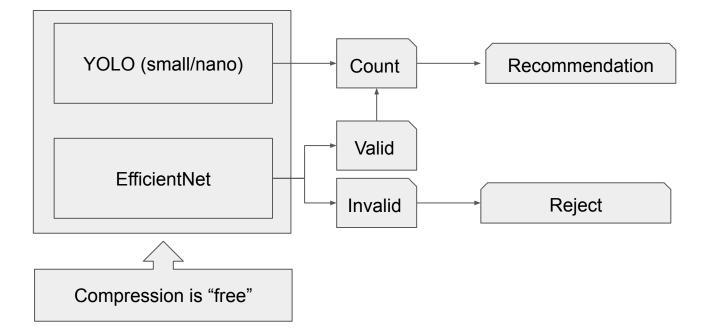
- Very strong numbers from best-performing teams
- Long tail is to be expected
- Our models performed better than most
  - Lots to learn from the crowd!



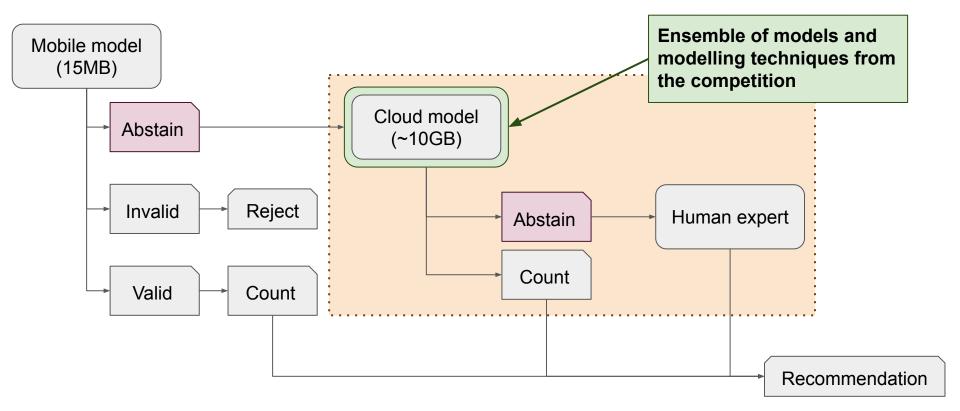
### Notable winning techniques

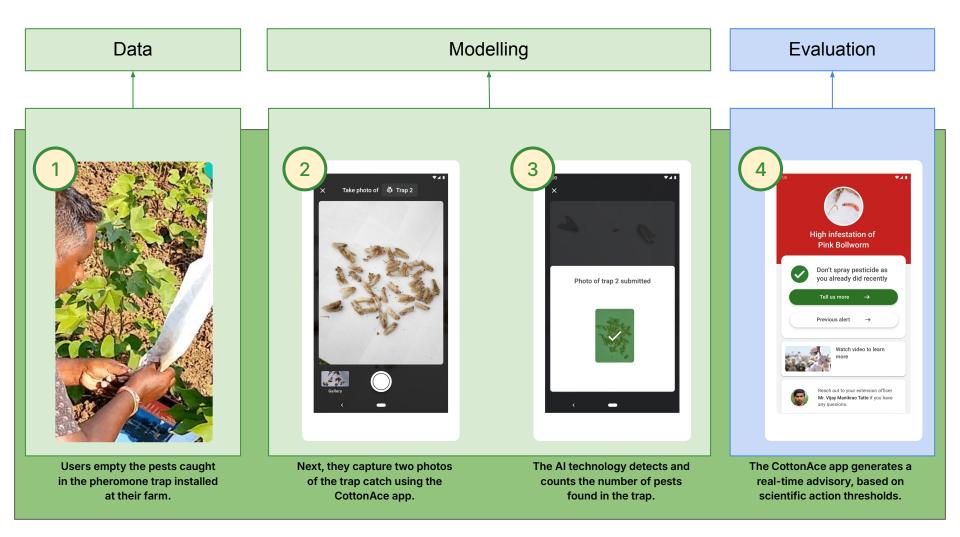
YOLO	<ul> <li>Four of the top six models used YOLO somewhere in their pipeline</li> <li> including first and second place</li> <li> transformers made a middling appearance (within the six)</li> </ul>	
Large images	Train resolution ranged from 1024 to over 2500!	
Augmentations	<ul><li>Mosaic</li><li>Mixup</li></ul>	
NMS magic	<ul> <li>NMS tuning is key (we knew this, but good get validation)</li> <li><u>Weighted Boxes Fusion</u> (WBF)</li> </ul>	
Ensembling	<ul> <li>Some used test time augmentation (TTA; we'd been experimenting with this, good to see examples)</li> <li>Cross validation to improve confidence</li> </ul>	

### System workflow (2023)



### System workflow extended (2023)



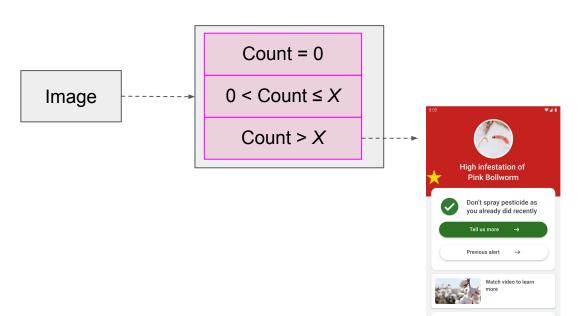


# User-centric evaluation

- Modelling produces counts
- Business logic produces categorical RED/Yellow/Green alerts

Business logic can vary, and can be difficult to model directly

... but it's prudent to keep in mind during tuning and evaluation



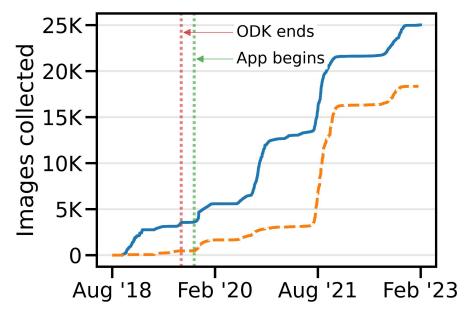


### Open source data: facilitating collaboration

#### Overview

- 36K+ images
- Captured during formal data collection and app deployment
- Mix of
  - pink and American bollworms
  - Images without bollworms





### Low barrier to entry

\$> git clone https://github.com/WadhwaniAI/pest-management-opendata.git

- \$> cd pest-management-opendata
- \$> aws s3 sync --no-progress s3://wadhwaniai-agri-opendata/ data/
- \$> ./bin/to-ultralytics.sh -d data -o /desired/output/location
- \$> git clone https://github.com/ultralytics/yolov5.git
- \$> cd yolov5
- \$> python train.py --data /desired/output/location/config.yaml ...

from datasets import load\_dataset # HuggingFace!
dataset = load\_dataset('wadhwani-ai/pest-management-opendata', streaming=True)

### Scaled Social Impact

- Reduction in pesticide usage by **20%**
- Translates to increase in profit by **25%**
- Reached 500K farms in 2023
- Adopted by National Pest Surveillance System (NPSS)
- Awards and Recognition
  - \$3.3M grant from Google.org 2023
  - Global Change Award Winner H&M Foundation 2021
  - Fast Company World Changing Ideas 2021
  - \$120K grant from GIZ for kaggle-like competition

## **Building AI Solutions**

### Beginning AI for Social Impact - Story (~2017)

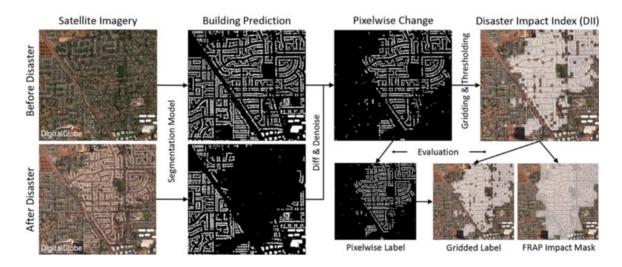


Figure 1: Flow diagram of our proposed approach for disaster impact analysis. We run pre-trained CNN on satellite imagery before and after disaster, compare the change in extracted man-made feature, then compute Disaster Impact Index (DII) to understand impact of each area

Doshi, J., Basu, S., & Pang, G. (2018). From Satellite Imagery to Disaster Insights. Al for Social Good, Neural Information Processing Systems (NeurIPS) Workshop.

Boin, J.-B., Roth, N., Doshi, J., Llueca, P., & Borensztein, N. (2020). Multi-class segmentation under severe class imbalance: A case study in roof damage assessment. Humanitarian Assistance and Disaster Response, NeurIPS Workshop.

### Wadhwani Institute for Artificial Intelligence



Non-profit dedicated to making positive social impact

- By developing and deploying AI/ML based solutions
- Focusing on underserved communities in India and other developing countries

#### Inaugurated in February 2018



### How to pick a problem? 8 Questions

**Impact potential:** Is it a big problem? What is the specific problem that AI is expected to solve, and in what settings? Will solving that specific problem have large enough impact?

**AI feasibility:** Is an AI-based solution feasible, technically? Are there logical and scientific reasons to believe the envisioned AI model is possible? Does the data exist or acquirable?

**AI necessity:** Will AI be sufficiently better than other (potentially easier) approaches to warrant the (additional) effort?

**Full solution + System design:** Will AI make enough difference, given other issues? What else needs work (workflows/processes upstream, downstream, in parallel) for the full system-integrated solution to have expected outcomes?

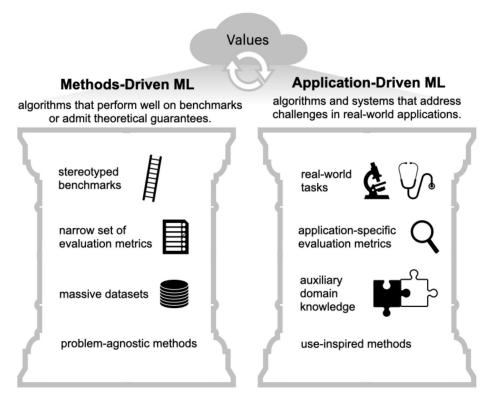
Acceptance & Usage: Will stakeholders (chooser, payer, user, beneficiary) accept it and use it the way it's envisioned?

**Partners:** Who are the partner orgs to co-innovate, co-deploy, iterate, pilot with? Do they have the complementary competencies required?

**Scaling:** Who are the owners, programs and pathways for scaling? Can the all the (technical and non-technical) components of the solution scale to ensure financial and operational feasibility?

**Why Us:** What makes us uniquely qualified to work on this? Is this the most highest leverage work I could be working on?

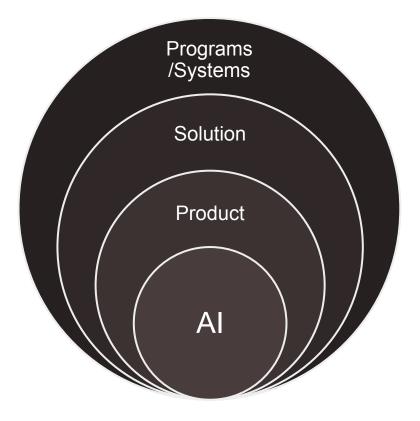
### Methods Driven ML vs Application Driven ML



Source: https://arxiv.org/abs/2403.17381

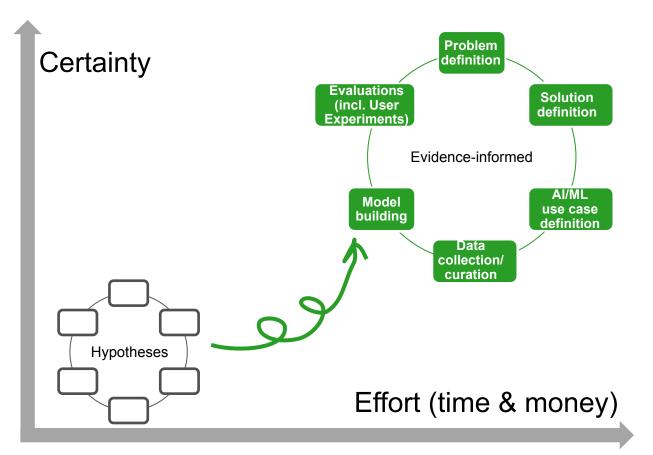
### AI Solutioning

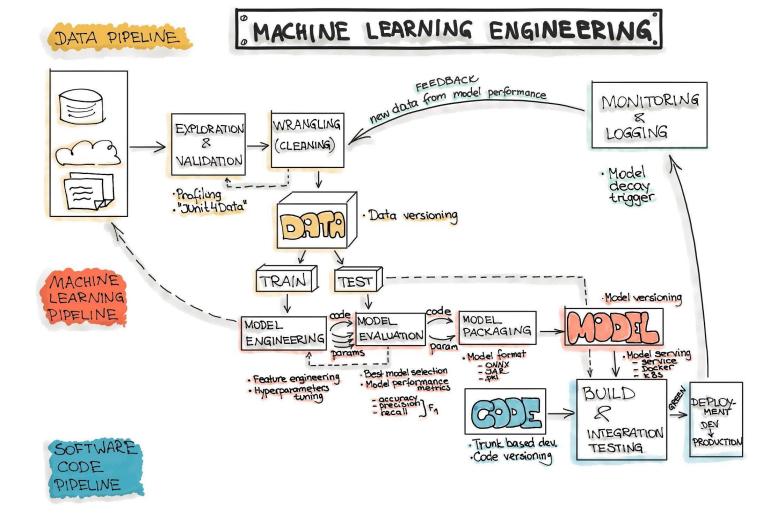
AI can play a potentially transformative role, but only **as part of complete** solutions integrated with systems for impact at scale



A mental model to help imagine the real process of building At AI-based solutions responsibly

The whole process is about making key interconnected choices with increasingly greater certainty, iteratively, while figuring out trade-offs and generating evidence.







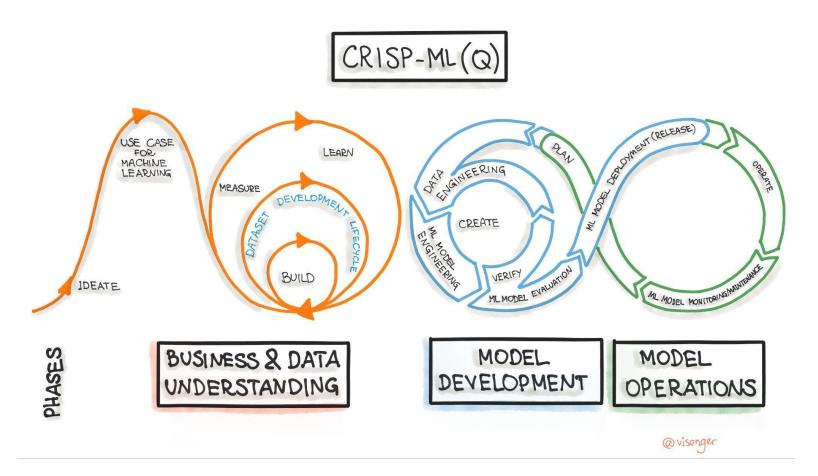


Fig. Source

### **Principles and Heuristics**

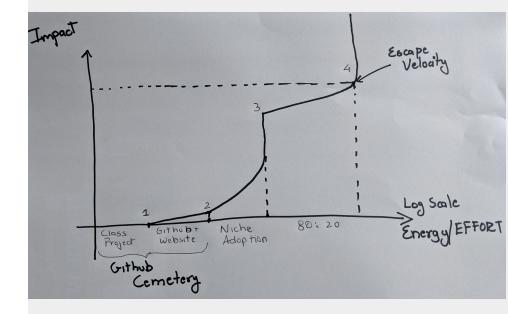
- 1. Imperfect solution to a right problem > perfect solution to a wrong problem
  - a. Breadth-first. Not depth-first
- 2. Premature optimization is the curse of ML (and any field)
  - a. Start simple.
  - b. Simple, low-tech debt solution to complex but highly performant
- 3. No perfect launch. It is a journey.
  - a. Iterate quicker. Fail faster.
  - b. Prioritise where to improve, not what you think is important
- 4. "So what" > Why > What > How (solution)
  - a. Insist on "So What?" seven times.
  - b. But we often start with a solution (or a technology)
- 5. Err on "data" side.
  - a. Collect more but purpose driven (even if the purpose is anticipatory).
- 6. Outputs will be wrong
  - a. Abstain when not sure (can the UX support it?)
    - i. Models need not make decision all the time
    - ii. Abstention is a lever, in addition to "scope (functionality)", "resources (time, compute, human)", "quality".
    - iii. Design is about tuning these four degrees of freedom via negotiation.
- 7. Not all decisions are equal.
  - a. Cost-aware decision making.

Source: Slides of Soma Dhavala

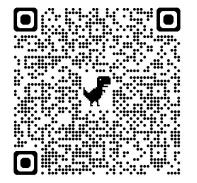
### How develop taste for problems?

- Opinionated First Principled Framework
  - Find your **values**, what change do you wish to see in the world?
    - You must be willing to live that yourself first
    - Boil it down to 2 or 3 values
  - Given a set of values, find large 'unsolved' domain
    - Hill you are willing to 'die' on
    - https://encyclopedia.uia.org/problems/1
    - Climate Change, Mental Health, Financial inclusion, Epidemics, Social Injustice, Drug Discovery Misinformation, etc
  - **Pursue it** with all your time, energy and attention
    - Be open minded on the 'how' to get there. Startup, Non-profit, Academia, Content Creator etc
    - Immerse yourself within these communities or build your own
    - Aim higher than your imagination. Though pursue it with integrity, humility and honesty
    - Don't chase status, awards, recognition. Make enough money to continue to pursue this.

# Effort vs Impact Curve



## Thanks! jigarkdoshi.com



### Outline

- Jigar's Journey into Social Good
  - Story time with Disaster Mapping and Joining Wadhwani AI
- Problem Selection
  - 8 + 1 Question Framework
  - Innovative Taste
- LLM for FLWs
- Anthropometry
- TB & Covid Cough
- Building Solution Journey
  - How to
- Satellite Imagery
- Pest Management
- Future: Agents for Public Health System