Transforming Rapid Diagnostic Tests into Trusted Diagnostic Tools in LMIC using AI

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BACKGROUND

- In low and middle-income countries (LMICs), Rapid Diagnostic Tests (RDTs) are often the only way to diagnose diseases such as malaria, HIV, and COVID efficiently and cost effectively.
- Large and always-connected AI-based mobile solutions are difficult to implement in LMICs due to limited resources available on commonly used phones and unstable Internet connectivity.

CHALLENGES

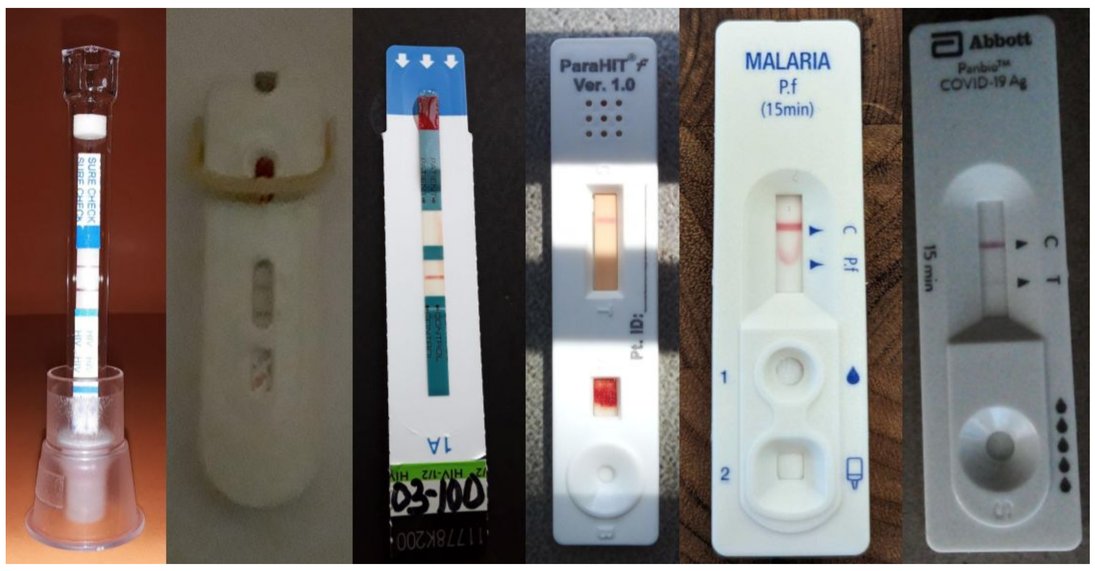
Challenges photographing RDTs in real-world scenarios:

• different lighting conditions	• faint test lines
• blurred images	• blood or staining on the RDT
• rotated RDTs	• obstruction by barcodes or QR codes.
• skewed images	• adversarial backgrounds

METHODOLOGY

- The HealthPulse AI training pipeline consumes the images and associated labels, producing multiple CV models that work together including:
  - An object detector that:
    - Locates the RDT
    - Locates the RDT sub-parts within the image
    - Identifies the RDT type.
  - A second object detector that examines the RDT result window and locates the test and control line regions.
  - A classifier that examines each line region of the result window and outputs line presence probability.
  - An Image Quality Assurance (IQA) pipeline that flags adverse image conditions like blur, low lighting, and over- exposure.
- Google's MediaPipe (GMP) framework is used to route images through this sequence of models and return results.

RESULTS



RDTs for HIV, Malaria & Covid. Adversarial conditions seen in the real world that make RDT interpretation more challenging. Left to right : *Sure Check HIV 1/2 Assay* with glare on test area, *Mylan HIV Self Test* low resolution image, *Abbott Determine - HIV 1/2* rotated image, *ParaHIT-F Malaria RDT* with a shadow on test area, *SD Bioline Malaria Ag Test* with staining on result window, *Panbio COVID-19 Ag Rapid Test* with a faint test line.

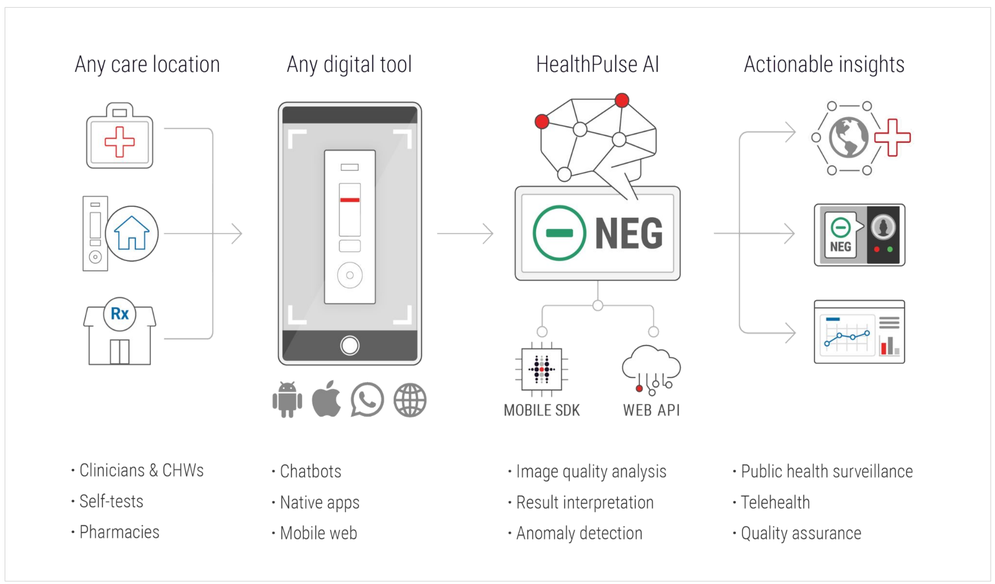
The RDTs in the figure above differ in material type, shape, size as well as location of test lines. We observe across all three diseases, using IQA has a positive impact on model performance. The IQA pipeline filters out images which the model might fail on, thus helping the overall performance. Another advantage of IQA is the high degree of overlap with human interpretability. The IQA filter can provide real-time training on how to get better photos. For each dataset in the table below, the classifier accuracy with IQA exceeds human accuracy reading the test result in the field.

Condition Dataset	Dataset Size	Without IQA*	With IQA*	Health Workers Score
COVID-19	731	0.993	0.993	N/A
HIV	888	0.981	0.988	N/A
Malaria Set-1	2479	0.963	0.964	0.953
Malaria Set-2	4205	0.938	0.949	0.929

*Weighted F1 Score and impact of IQA on model performance, *Image Quality Assurance (IQA) Pipeline*

CONCLUSION

- We developed the HealthPulse AI system to serve LMIC with the following capabilities:
  - Run with intermittent or no Internet connectivity.
  - Run with operating system as old as Android 6.
  - Run on phones with total device memory as low as 1 GB.
  - Flag adverse photo capture conditions.
  - Provide accurate results for commonly used RDTs, even for faint line identification.
  - Work across RDTs of different types, shapes and sizes.
  - Run on images captured without use of any stands, controlled backgrounds, or lighting.
- We use a modular pipeline with multiple smaller models (versus one large model) to reduce memory requirements and enable focused and flexible training of models that can be generalized for a wide range of RDT types.



HealthPulse AI can substantially improve access to timely quality care across a variety of private, public, community, and self-testing use cases.

HealthPulse AI algorithms for malaria, HIV, and COVID tests are used in programs, pilots, and studies across Kenya, Nigeria, South Africa, Côte d'Ivoire, Uganda, Rwanda, and Benin. Financial support for Audere's work was provided by the Bill and Melinda Gates foundation, grant numbers INV-007492 and INV-054895.