AI based Microscopy diagnosis of Malaria

AI for Health Workshop 2019

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Microscopy Diagnosis

Figure: Gold standard for diagnosis of malaria is a microscope

Health diagnostic burden

Currently in Uganda, and many developing countries

- Malaria has been reported as one of the leading cause of death accounting for over 27% of lives of Ugandans
- Patient in big numbers wait to be diagnosed.

Currently in Uganda, and many developing countries

- Most of these countries don't have enough trained lab technicians.
- In Ghana, 1.72 microscopes per 100,000 population, but only 0.85 trained laboratory staff per 100,000 population .

Microscopy Diagnostic challenge

Currently in Uganda, and many developing countries

- SOP requires not to view more than 20 slides a day
- IMicroscopy is eye straining

Concept detail

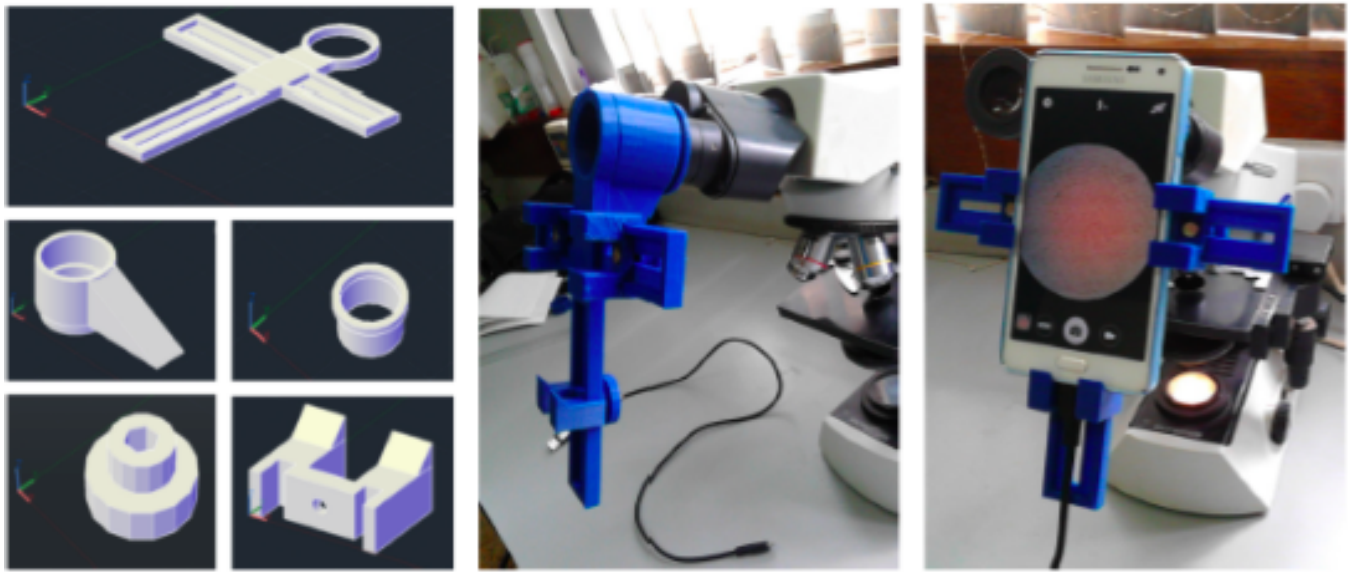
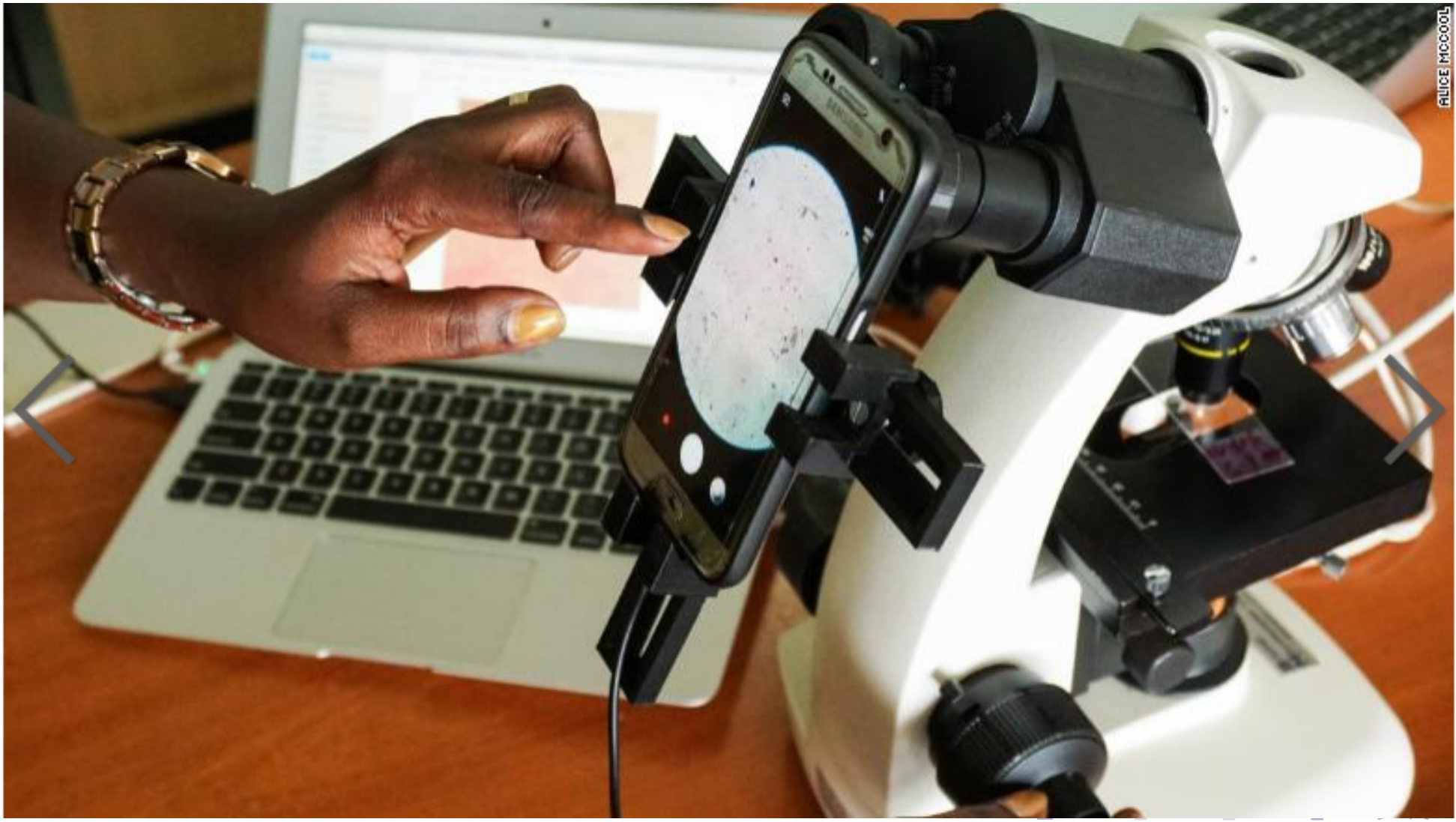


Figure: Adapter set up and attachment.

Concept detail

Concept detail



Captured image

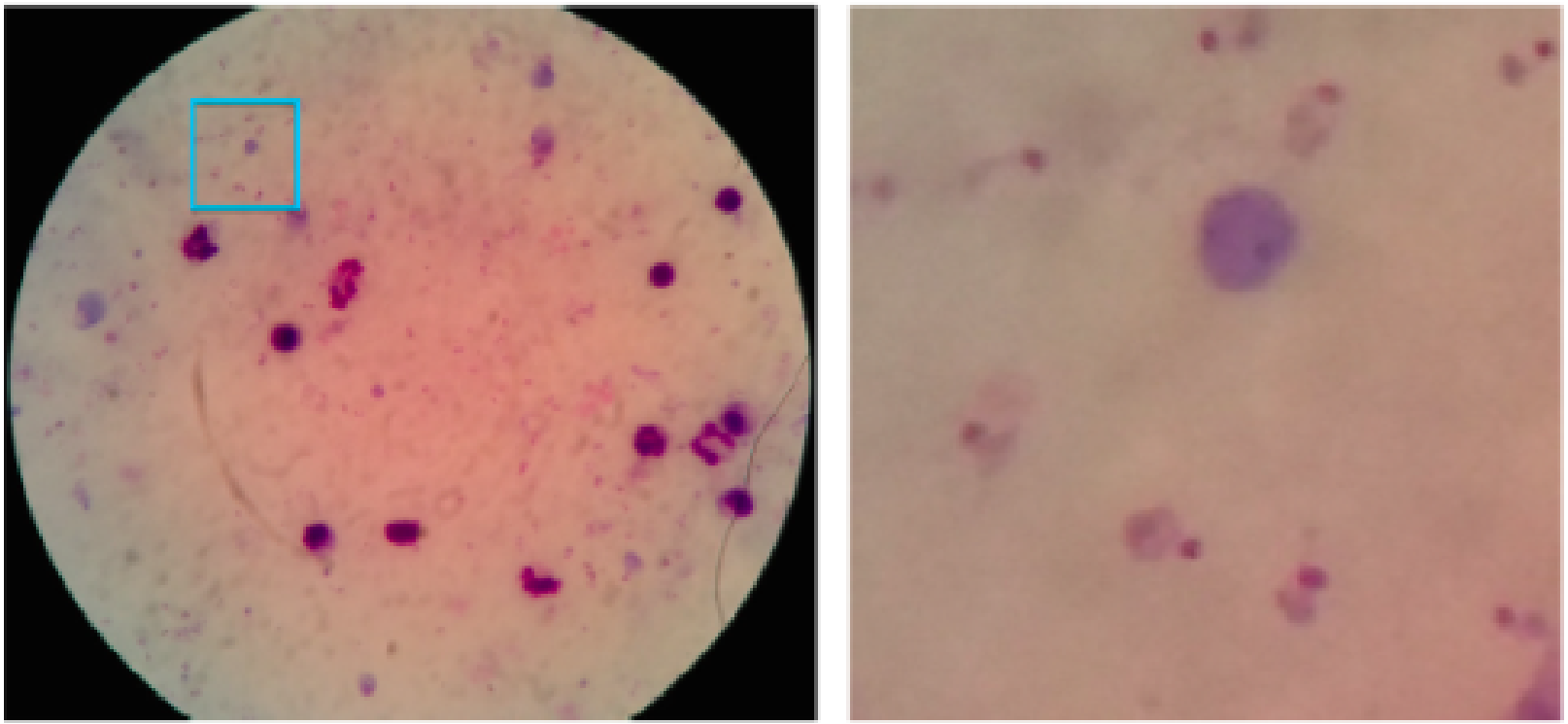


Figure: Malaria microscopic image captured with a smartphone.

Plasmodium detection accuracies

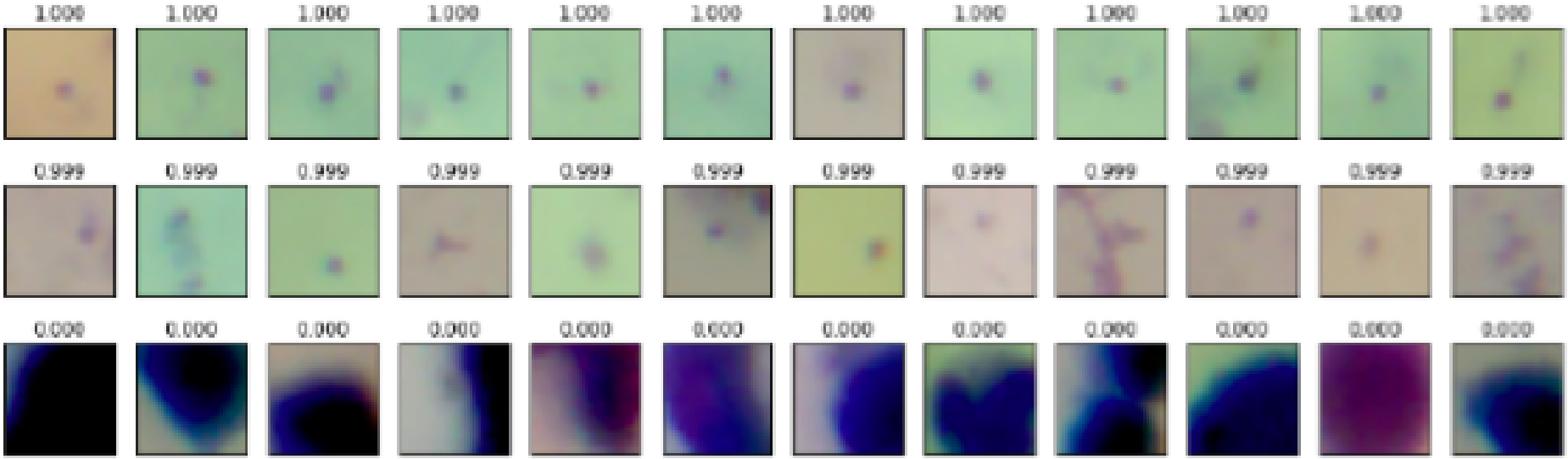


Figure: Plasmodium detection results.

ROC AUC for malaria, TB and intestinal parasites detection

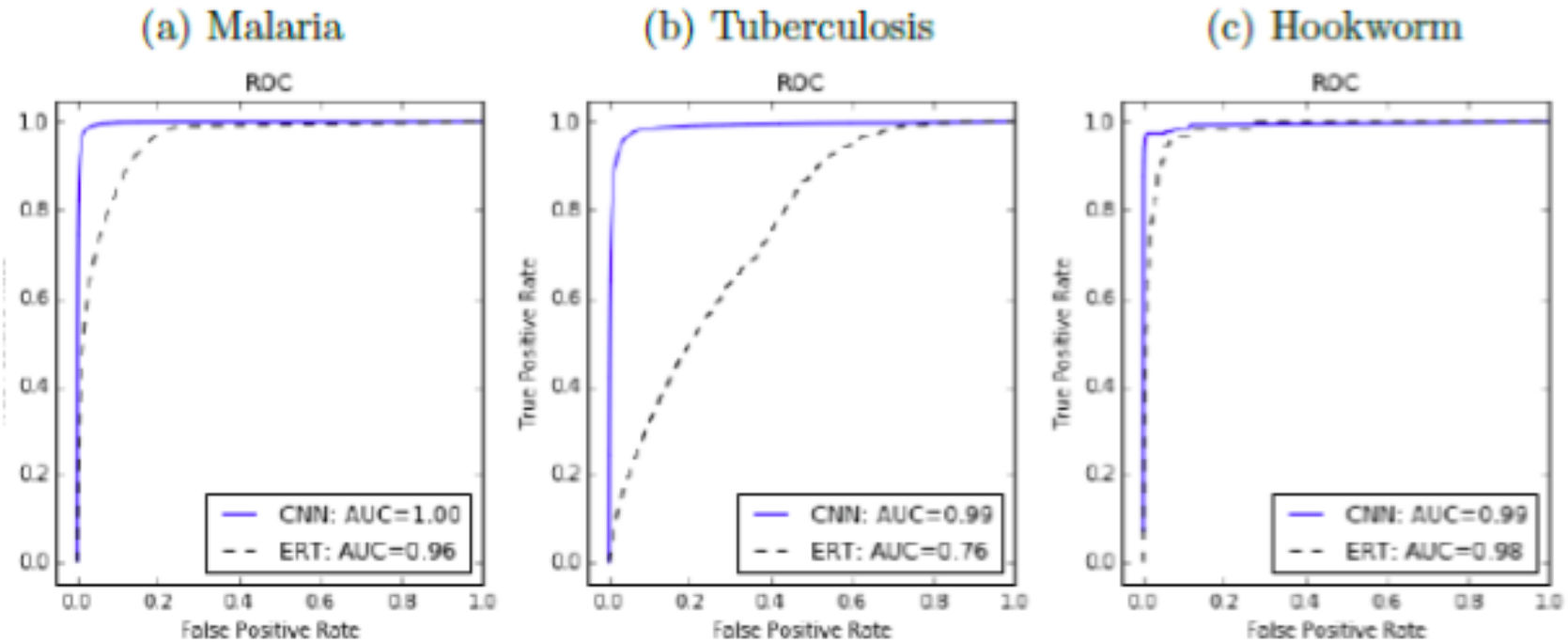
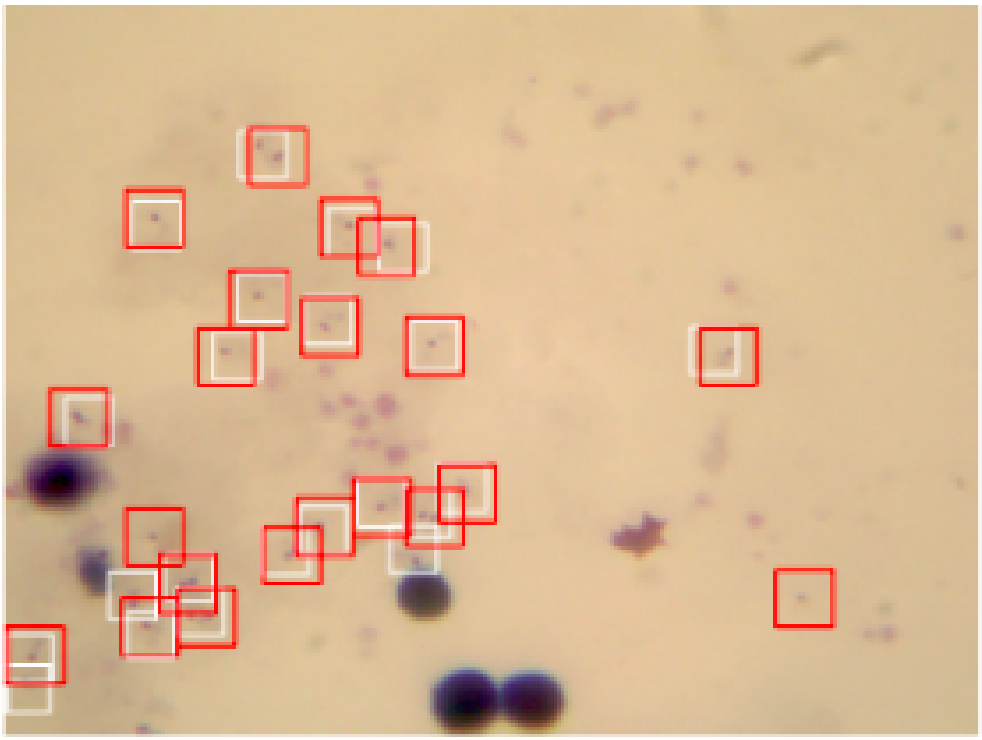
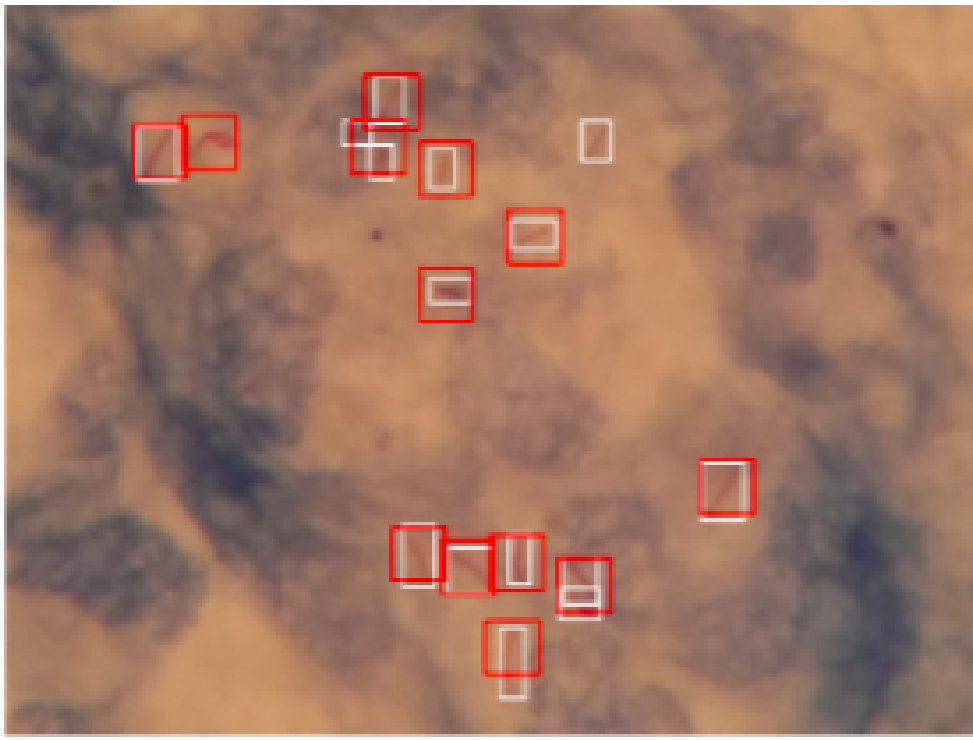


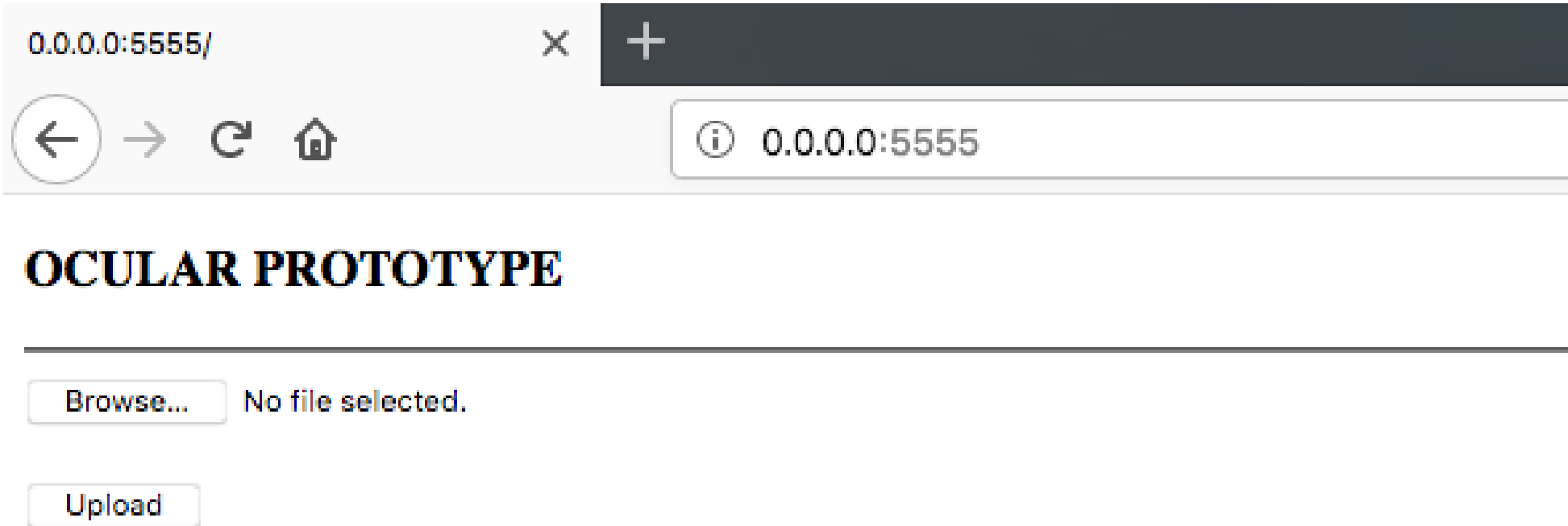
Figure: Deep learning ROC accuracies.

Detected Objects for plasmodium (left) and bacilli(right).





Server end app.



Server end app.

Figure: Before detection.

Server end app.

Figure: After detection.

Framework assessment requirements

Reasons to consider for an effective clinical framework;

- Representativeness in data
- Explainability
- Potential biases in the data.

Representativeness in data

Training data is from a different context;

- Obvious case: do not use European training data for medical diagnostics in East Africa.
- Less obvious case: Medical diagnostics data could use training data from East Africa for an algorithm in West Africa – may under-diagnose malaria.

Training data is imbalanced;

- Data that is not balanced in terms of pixel dimensions, shape, color etc may bias certain algorithms to favor certain groups

Explainability

Ethical coonsiderations;

- Do Organizations think of ethics when using data/outcomes from algorithms, resulting organizational values not being captured in outcomes.

Relevancy / Value;

- Should organizations be using AI and does AI provide enough value that offsets potential complications?

Transparency;

- How transparent are the algorithms/outputs?

Potential data Biases

Does your data have biases reflected in it? If so, your algorithms may amplify these biases;

- Due to poor annotations.
- Different image dimensions.
- Different environments under which the images were captured.

What can we do?

- Auditable algorithms
- Implement fairness
- Accountability and responsibility

Auditable algorithms

Bias is introduced at the algorithm level

- Developers are making decisions to choose between equity, accuracy, speed

Ensure that algorithms are auditable;

- Can they be monitored by external actors? How can you test the algorithms?

Fairness

Data will never be perfect. How will we deal with imperfect data?

- Getting better data
- Implementing fairness/equity at the algorithm level

Accountability and responsibility

What mechanisms can we add to make sure that we are holding ourselves and algorithms accountable?

- We work in complex situations and downstream effects are hard to predict
- Build in monitoring to make sure that we can adapt to and fix inequalities that result
- Above all, an AI Assessment Framework to guide AI for health Solutions.

Thank you!

Questions?