Artificial Intelligence Offers a Better Way to Diagnose Malaria

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Malaria is a widespread and life-threatening disease, especially in rural areas

HALF
Of the world's population is at risk from malaria.

214 MILLION CASES of malaria worldwide in **2015**

90%
Of malaria deaths occur in sub-Saharan Africa

60 SECONDS
How often a child dies from malaria.

0
Malaria is preventable and treatable.
No-one needs to die.

PROBLEM | METHODOLOGY | IMPACT

Malaria: An increasing threat to everyone

Global

Malaria thrives wherever the vector can survive, which is usually in tropical regions. However, with increasing global temperatures, it is suspected that the vector would soon be able to survive in Europe

Business

Many western businesses are expanding their activities to include Africa. Although many locals have developed just enough immunity to protect them from malaria, foreigners might not be so fortunate.

Travel

For example, in the United States, the Centers for Disease Control and Prevention (CDC) report 1,700 cases of malaria annually, majority of which are people who travel to countries where malaria is more common [can also be transmitted through blood transfusions & organ transplants]

The need for an automated malaria diagnosis process

Early Detection + Proper Diagnosis → Delivering reliable healthcare → Increasing chances of cure

Microscopic inspection

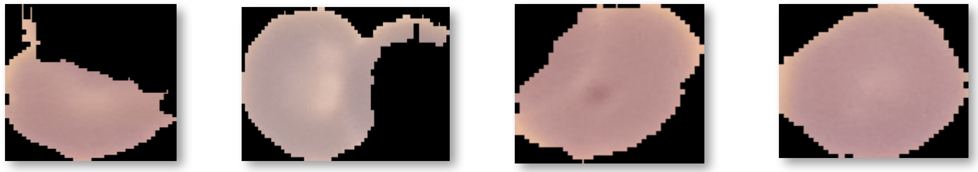
Inefficient	Low Accuracy	Specialized infrastructure	Specialized human resources	Lack of standardization
• Manual counting methods are very **long, tedious**	• **False-negative**: progression into severe malaria • False-positive: unnecessary use of drugs and suffering from side effects	• Inadequate and **frequently unavailable** in rural areas where malaria has a marked predominance		• Important for **testing for drug-resistance, measuring drug-effectiveness, and classifying disease severity** • Depends heavily on the experience and skill of the microscopist

Dataset

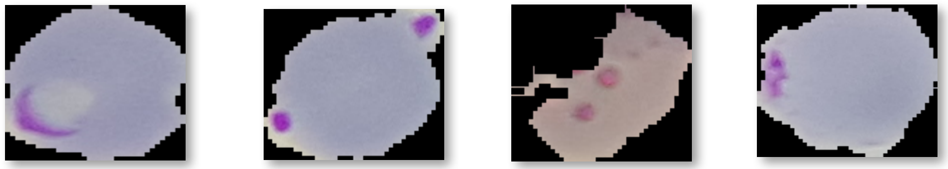
CREATE A CLASSIFIER TO DIFFERENTIATE BETWEEN INFECTED AND UNINFECTED CELL

27,560 images

50% uninfected cells

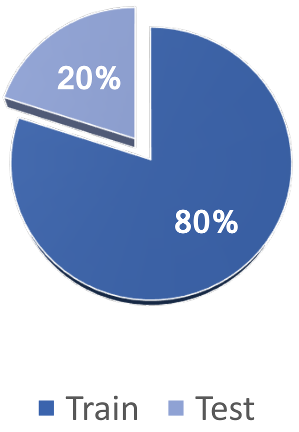


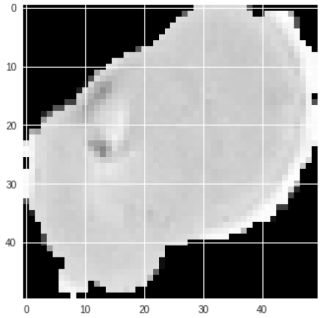
50% infected cells



Source: U.S. National Library of Medicine

Base Model - Logistic Regression



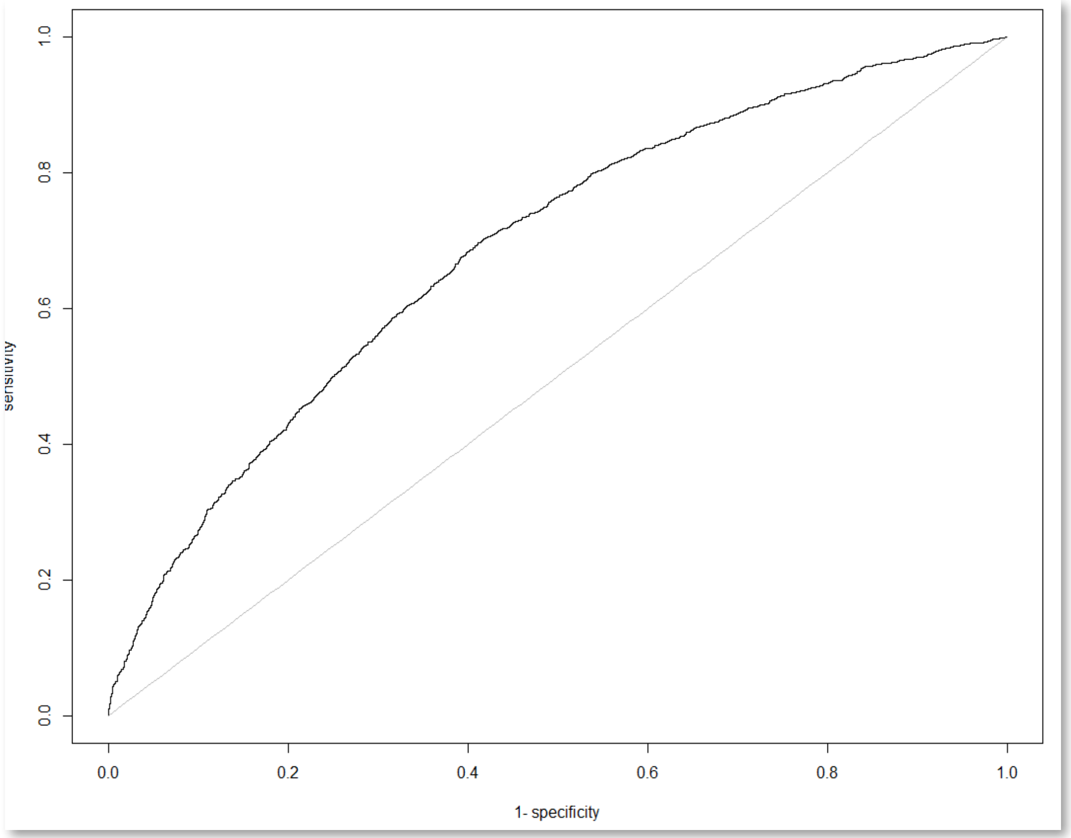


50x50 Grayscale

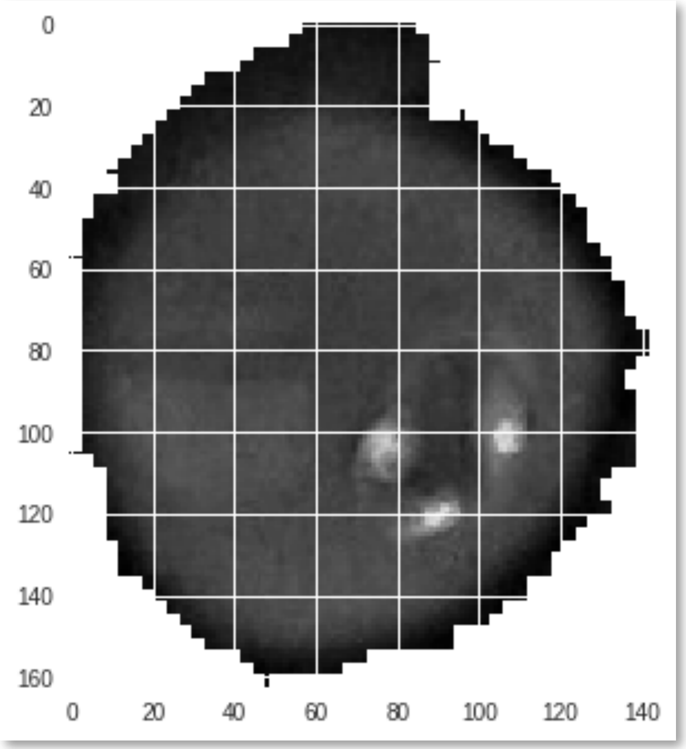
Flattened

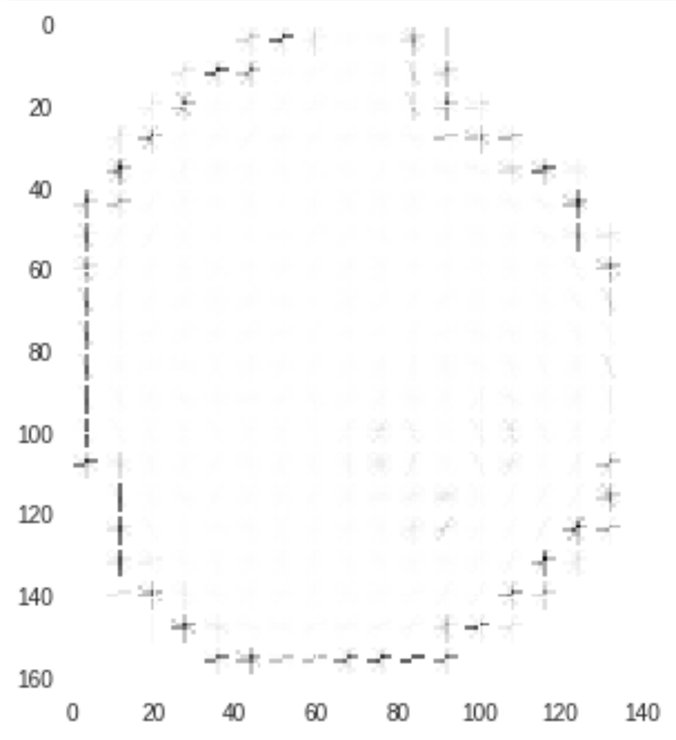
Input

Accuracy = 0.63, AUC = 0.69



Base Model - Feature Engineering: Histogram Of Gradients





Shape detection

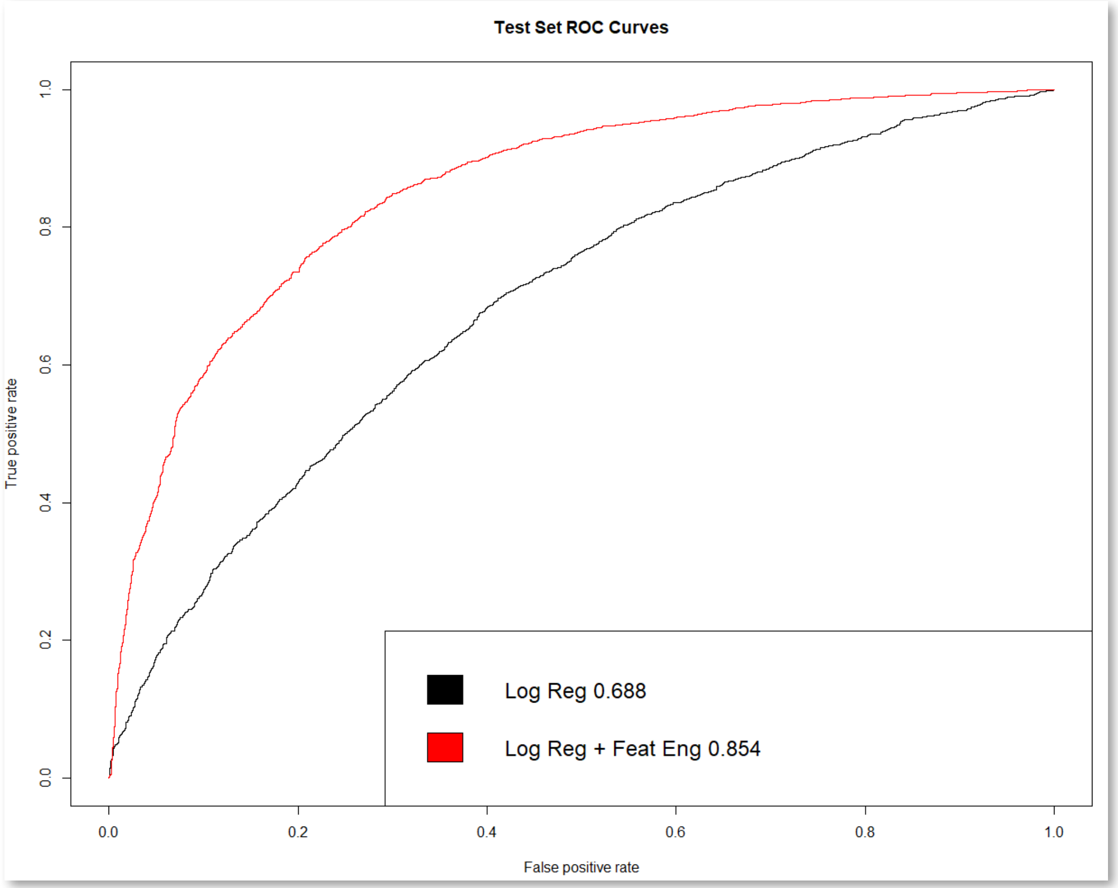
Reduce images from 2500 pixels to 800 features-> Faster model training

Base Model - Logistic Regression with HOG feature engineering

AUC: From 0.69 to **0.85**

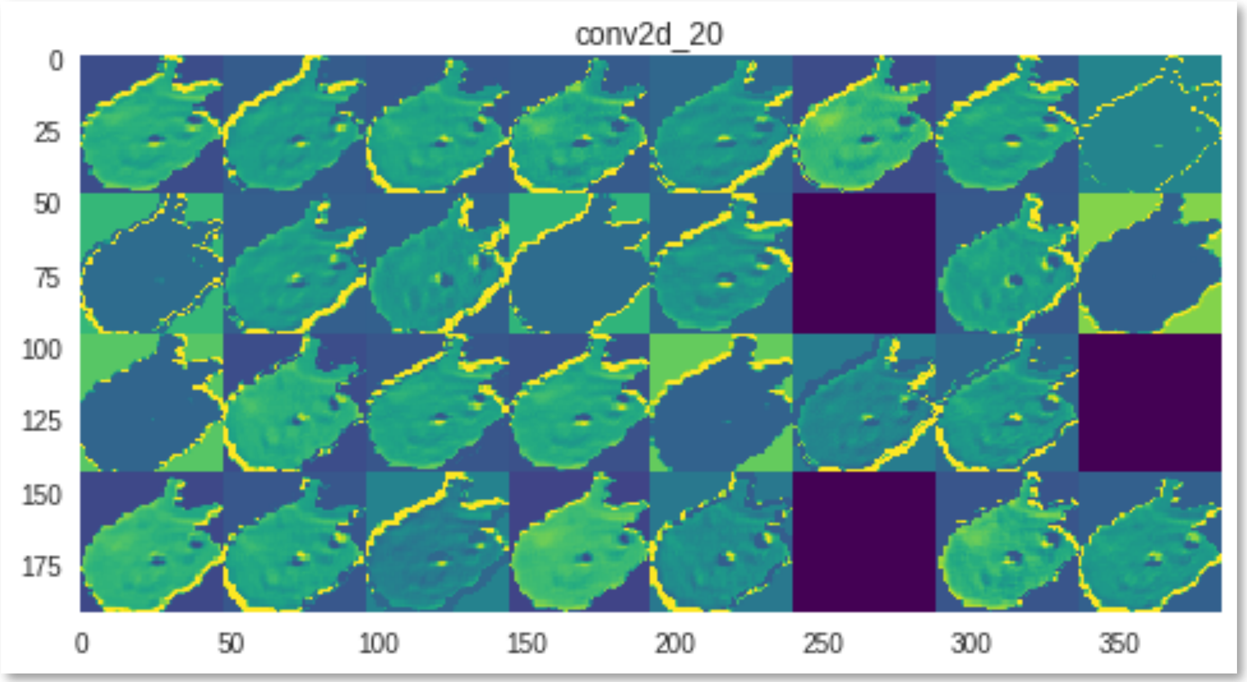
Accuracy: From 63% to **77%**
95% CI : (0.7621, 0.7844)

Feature engineering worked!



Convolutional Neural Network (CNN)

- CNNs allow us to build a classifier without doing the feature engineering ourselves.
- We can see edge detection working in the first layer of our CNN

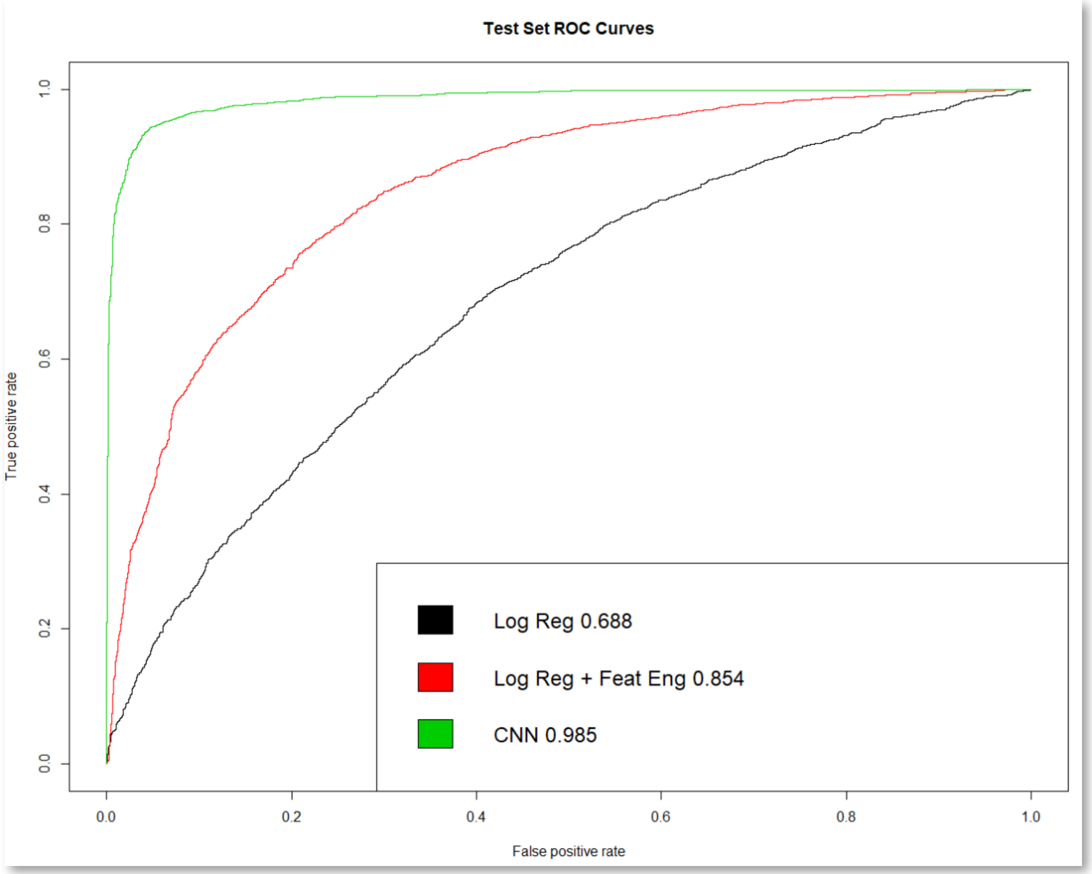


Convolutional Neural Network (CNN)

- Due to hardware limits, we trained a relatively simple Convolutional Neural Net

- **Accuracy: 92.7%**
  95% CI : (0.9206, 0.9345)

Impressive results!



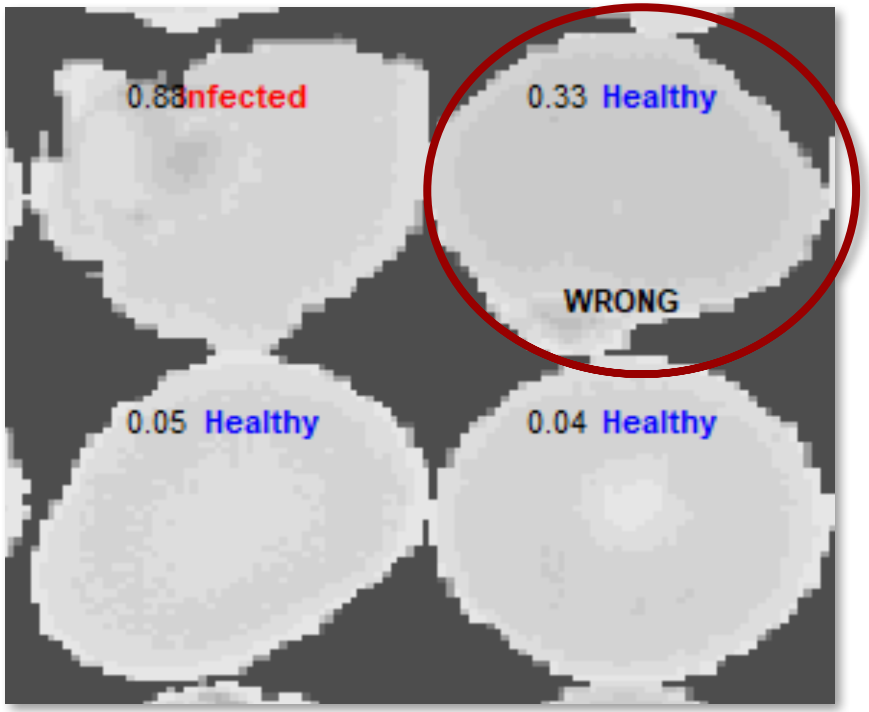
Setting the threshold of the classifier

- CNN assigns probability to each image
- Default threshold of 0.50
- >0.50 = Infected, <0.50 = Healthy

- It is extremely dangerous to misclassify an infected person as healthy (different costs)

- The percentage of infected correctly classified is known as "Sensitivity"

BAD

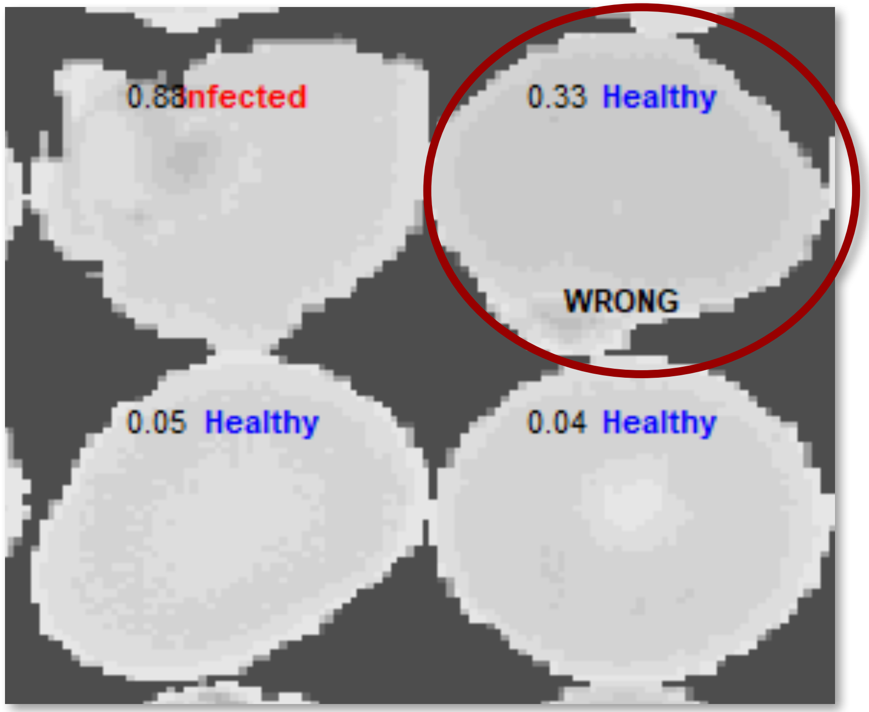


Setting the threshold of the classifier

What is the threshold to maximize

BAD

Sensitivity + Accuracy



Setting the threshold of the classifier

Threshold = 0.18

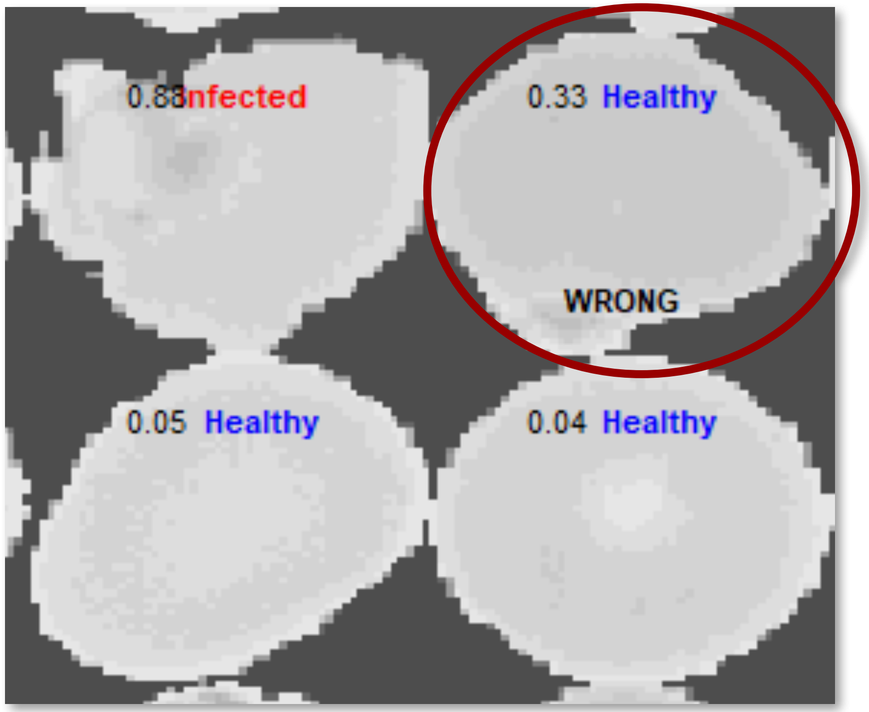
BAD

Sensitivity

88.2 -> 96.0%

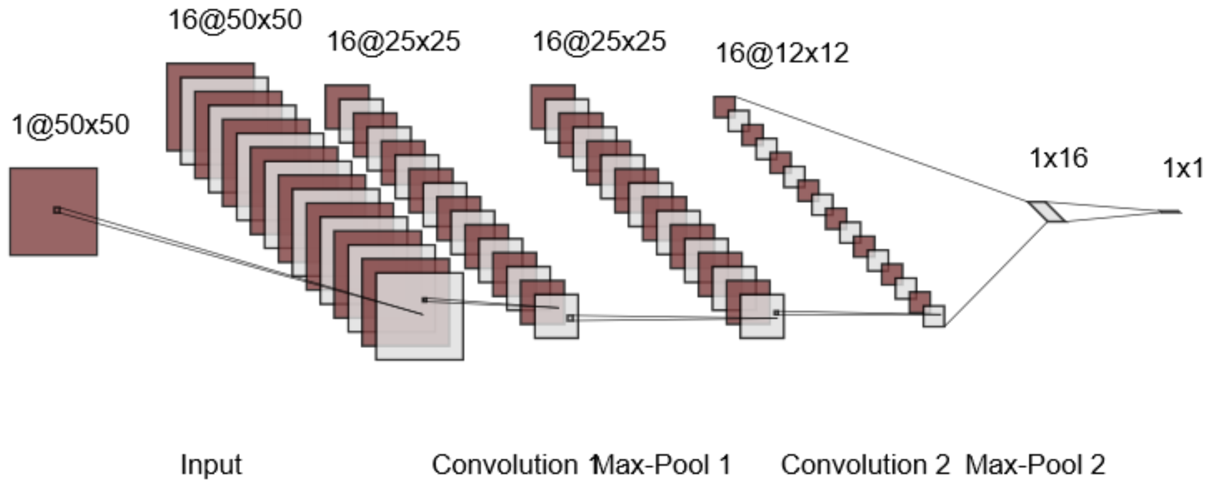
Accuracy

92.8 -> 93.4%



Model summary

Our CNN correctly identifies 96% of infected cells in an instant!



Comparison to Previous Work

Smaller Dataset

With a dataset of only **1,300** images, overfitting was highly likely.

Comparison:SVM

The results from the CNN were compared with Support Vector Machine(SVM) (92% accuracy).

98% Accuracy

Higher accuracy could be due to higher image resolutions and more computationally intensive CNNs (GoogleNet)

Larger Dataset

Our dataset was 20 times larger, which is more representative and makes overfitting less likely.

Comparison: Logistic Regression

We first used logistic regression and then feature engineering on our dataset, and compared the results to CNN.

93% Accuracy

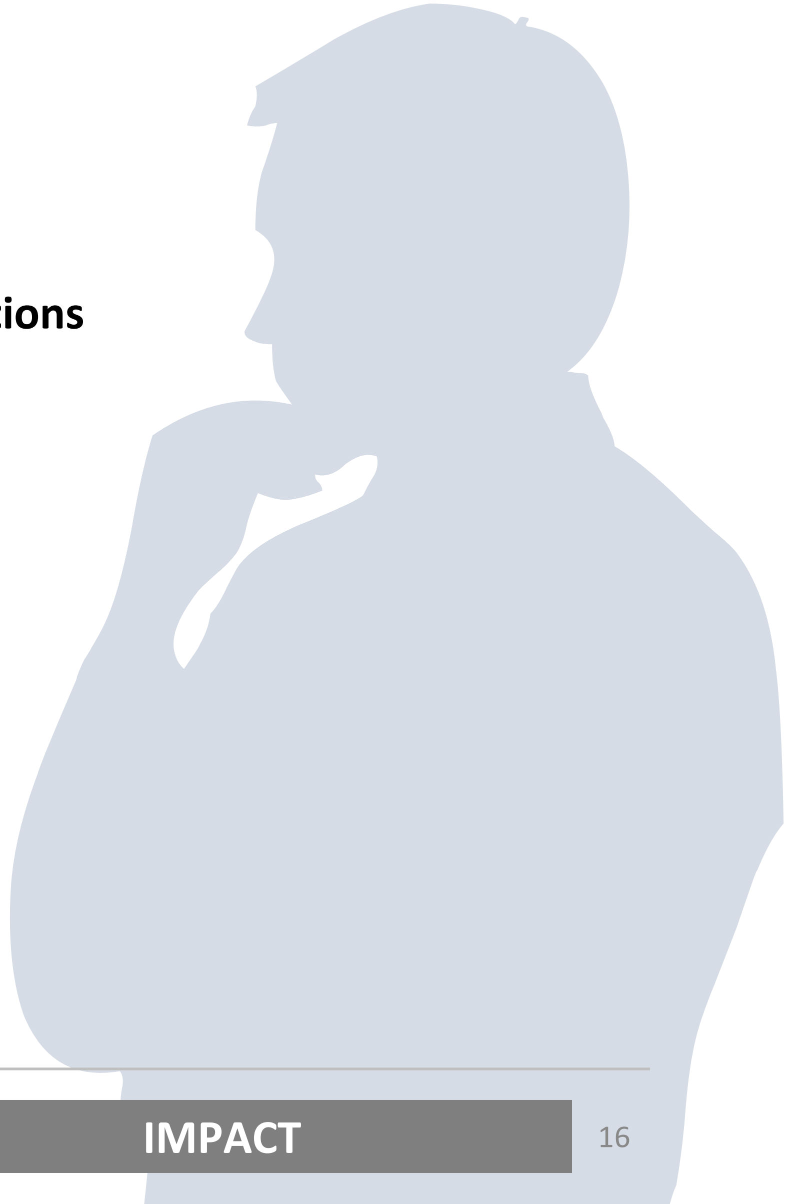
With an accuracy of 93% and sensitivity of 96%, we believe that this model is suitable for practical use.

THE UNIVERSITY OF ALABAMA IN HUNTSVILLE

THE UNIVERSITY OF ALABAMA AT BIRMINGHAM
Knowledge that will change your world

HEC PARIS

Limitations of our work



Trade-off between accuracy and computational power

Model cannot differentiate between malignant and benign infections

Limited computational power

Time constraints

Binary results

Conclusion

Automated Diagnosis

With automated diagnosis through CNN, we no longer have to rely on the experience of laboratorians.

Fewer Deaths

All this will lead to a reduction in the number of worldwide malaria-related deaths annually.

Higher Accuracy

Diagnoses will be more accurate, even in areas which are unfamiliar with the disease

Fewer false +/-

With fewer false positives and negatives, we avoid overprescription and delayed medication, which are major causes of malaria-related deaths.

Thanks for your attention.