DETECTING MALARIA IN RED BLOOD CELLS USING MACHINE LEARNING

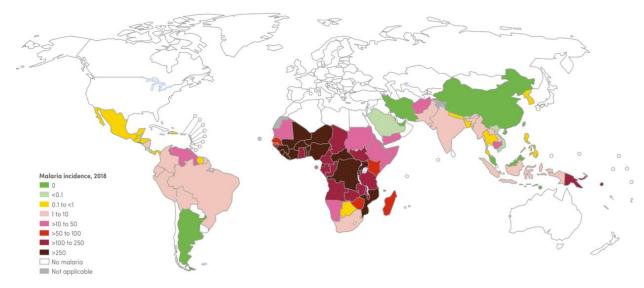
KIERNAN HARDING





THE PROBLEM

- Malaria has a major impact on global health
- 2019: estimated 229 million cases worldwide & 409,000 deaths [1]
- Only 5 countries account for more than 50% of all cases [1]
- Nigeria accounts for 27% of all cases [2] and has 34% of the world average GDP (per Capita) [3]
- Poor quality testing in less developed countries



Map of malaria case incidence rate (cases per 1000 population at risk) by country (2018) [2]

WHY TEST USING AI?

- Yearly, hundreds of millions of blood films are examined by a trained microscopist
- Microscopy involves manual counting of parasites in red blood cells
 - Timely
 - Costly
- Microscopists in less economically developed areas have poor-quality control settings and little resources
 - RDT test accuracy (among under 5's in 2015) is 79% [4]
 - Testing worrying low in children only 30% (e.g. Nigeria) [2]
- Lead to incorrect diagnosis
 - False positives and <u>false negatives</u>
- Faster testing
- Reduced workload
- More accurate



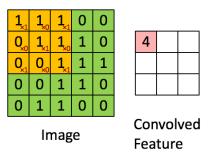
SUMMARISED AIMS & OBJECTIVES

- Design and implement a classification tool that identifies malaria parasites in pre-segmented red blood cells
 - Design a Convolutional Neural Network using reputable Python ML libraries
 - Through iterative testing, improve CNN model performance (accuracy) using ML techniques
 - When testing the application on unseen samples, the model should achieve a higher test accuracy than the RDT's diagnostic accuracy of 79% (among under 5's in Nigeria, 2015 [4])
 - Create a classification tool that is accessible via almost any device, enabling its use in less developed counties
 - The application should be simplistic to allow easy use for individuals with limited medical knowledge

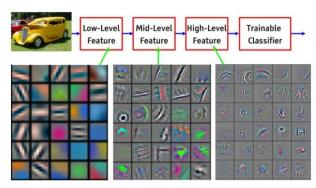


WHAT IS A CNN?

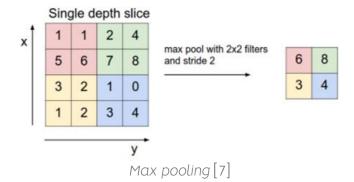
- Short for 'Convolutional Neural Network'
- Class of deep learning neural networks
- Learns similarly to a child inspired by the human brain
- Trained through backpropagation:
 - Forward pass pass input data through network as normal as caches values
 - Backwards pass go back through network and alter loss (similar to telling a child they're incorrect, which they then learn from)
- Different types of layers:
 - **Convolutional** identifies features in images, such as straight lines and curves, aids learning process (becoming less abstract over time)
 - Activation function (e.g. ReLU) aids the network to learn complex patterns in the data increase non–linearity (ReLU: returns 0 if negative and value x if positive)
 - Pooling (e.g. max pooling) reduces sample size and thus speeds up processing
 - Fully connected essentially the output layer (provides probabilistic values)



Convolution [5]

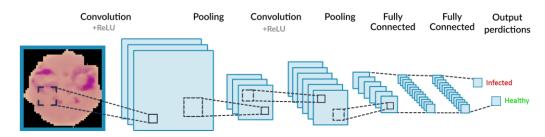


Convolved feature maps [6]



CREATING A CNN MODEL

- Splitting the dataset into training, validation and testing ($^{\sim}$ 80/10/10)
- Preparing the dataset for training rescaling
- Created a convolutional neural network model in Python using TensorFlow and Keras
 - 3 main layers and an output layer (the fully connected layer)
 - These layers include: convolutional, activation (ReLU), pooling and fully connected
- Greyscale, colour...



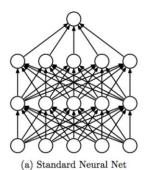
Example CNN model architecture

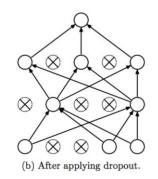
Final model architecture

Layer (type)	Output	Shape 	Param #
rescaling (Rescaling)	(None,	100, 100, 3)	0
conv2d (Conv2D)	(None,	100, 100, 32)	896
activation (Activation)	(None,	100, 100, 32)	0
max_pooling2d (MaxPooling2D)	(None,	50, 50, 32)	0
dropout (Dropout)	(None,	50, 50, 32)	0
conv2d_1 (Conv2D)	(None,	50, 50, 32)	9248
activation_1 (Activation)	(None,	50, 50, 32)	0
max_pooling2d_1 (MaxPooling2	(None,	25, 25, 32)	0
dropout_1 (Dropout)	(None,	25, 25, 32)	0
conv2d_2 (Conv2D)	(None,	25, 25, 32)	9248
activation_2 (Activation)	(None,	25, 25, 32)	0
max_pooling2d_2 (MaxPooling2	(None,	12, 12, 32)	0
dropout_2 (Dropout)	(None,	12, 12, 32)	0
flatten (Flatten)	(None,	4608)	0
dense (Dense)	(None,	128)	589952
activation_3 (Activation)	(None,	128)	0
dense_1 (Dense)	(None,	2)	258
Total params: 609,602 Trainable params: 609,602 Non-trainable params: 0			

IMPROVING PERFORMANCE

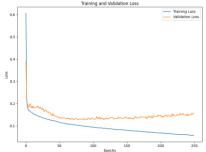
- Iteratively improved performance by evaluating a current model's validation accuracy
- Machine learning techniques to reduce overfitting and improve model performance:
 - Data Visualisation
 - Different perspectives, easy comparisons
 - Data Augmentation
 - Rotate, flipping, translation, scaling...
 - Regularisation
 - Applying dropout
 - Optimizer Adjustment
 - Adam, SGD, RMSprop
 - Feature Map Visualisation
 - Identify key areas that are detected



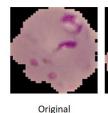


Dropout representation [8]





Final CNN model training graph



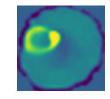


Rotated 90°



Rotated 180°





Data augmentation

Rotated 270°

Feature map sample

EVALUATION/MILESTONE RESULTS

- I evaluated the performance by calculating the model accuracy
- I iteratively improved on my model performance
- The model achieves a higher test accuracy than the RDT's diagnostic accuracy of 79% (among under 5's in Nigeria, 2015 [4])
- NIH only achieved ~ 2% higher accuracy in a similar project

Accuracy =	TrueNegatives + TruePositive
Accuracy –	TruePositive + FalsePositive + TrueNegative + FalseNegative
	Accuracy equation [9]

Model	Validation Accuracy	Test Accuracy
Greyscale (Interim)	94.2%	71.4%
Initial Colour	93.6%	93.3%
Colour Model (Final)	96.2%	95.6%

UI - WEB APPLICATION

- Use of web development to increase the applications accessibility in remote areas (localhost)
- No specific requirements (e.g. android application = limits reach)
- Uses the Flask library to implement the Keras CNN model into a web application
- Bootstrap styling...
- Simple to use and navigate
- Takes an image input of a blood sample
- Classifies and outputs whether the sample is infected

















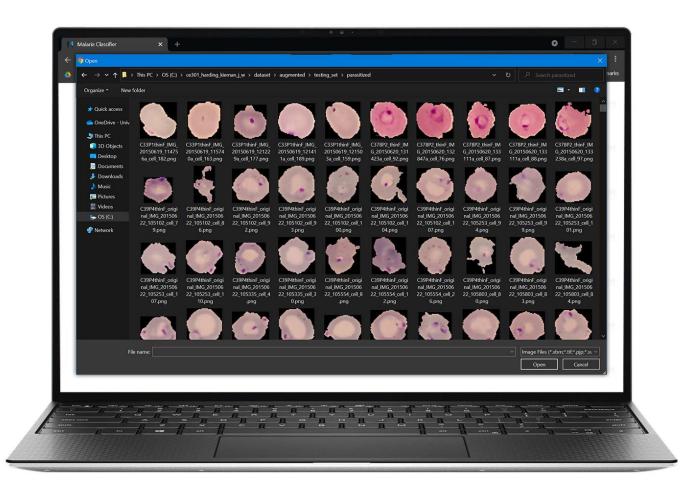


- A web application that includes a back-end machine learning classifying model
- Can be used on any device with an internet browser
- Live examples of infected blood cells being classified
- Live examples of healthy blood cells being classified

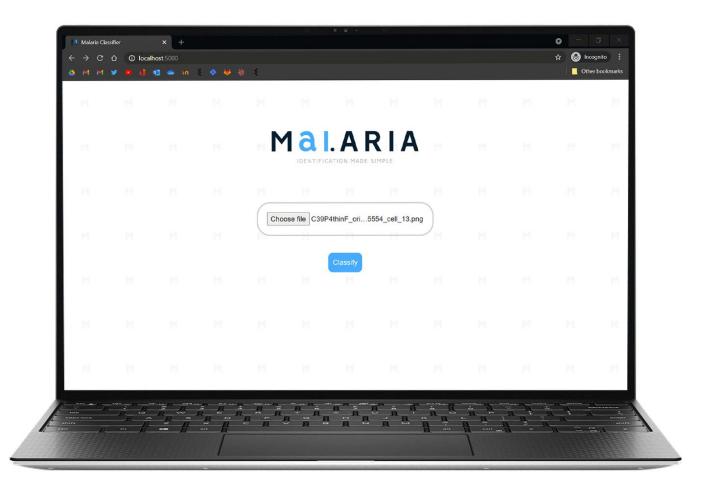
1. The home page



2. Choosing the presegmented red blood cell to classify



3. The sample has been selected



4. The 'classify' button has been clicked and the sample is being classified



5a. The classification output for an infected sample



5b. The classification output for a healthy sample



DID I MEET MY AIMS & OBJECTIVES?

 Design and implement a classification tool that identifies malaria parasites in pre-segmented red blood cells



Design a Convolutional Neural Network using reputable Python ML libraries



Through iterative testing, improve CNN model performance (accuracy) using ML techniques



• When testing the application on unseen samples, the model should achieve a higher test accuracy than the RDT's diagnostic accuracy of 79% (among under 5's in Nigeria, 2015 [4])



 Create a classification tool that is accessible via almost any device, enabling its use in less developed counties



• The application should be simplistic to allow easy use for individuals with limited medical knowledge



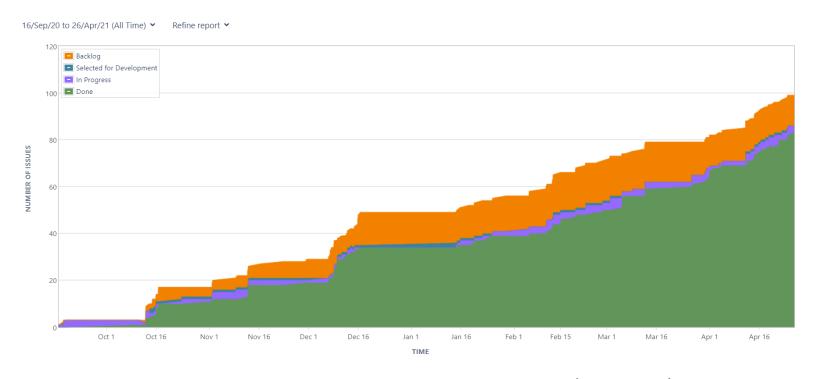
INTERIM → "TIMELINE OF FUTURE OBJECTIVES"

Improve my convolutional neural network model through research and	into my website to improve usability across all devices	Improve the visual styling of the user interface	Slack for any issues encountered before the submissions
structured testing (e.g. add colour) 8/2/21	22/2/21	8/3/21	17/3/21

17/3/21 – Open Day Submissions

USE OF JIRA

- Consistent use of Jira
- Use of tasks and subtasks to add detail
- Comments to document updates/plan future tasks

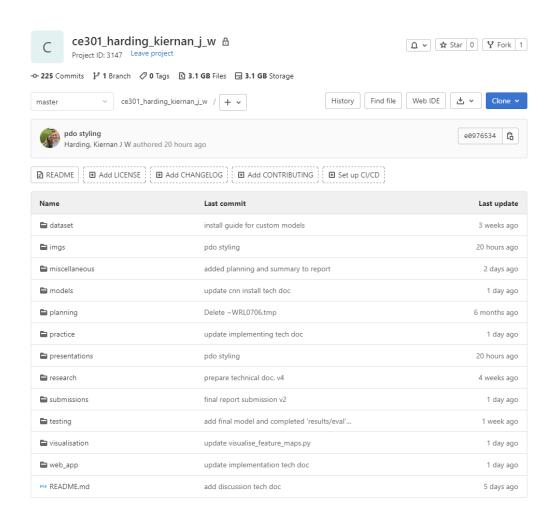


A cumulative flow diagram of issues from Jira (25/4/2021)

USE OF GIT

- Consistent use of Git
- Regular commits to Git for:
 - Significant changes
 - Keep important work backed-up!
 - Small required alterations
- Short, meaningful commit messages

 Use of .md files to keep a diary of milestone achievements and each CNN model's performance



A snapshot of my Git repository (1/5/2021)

MAIN ISSUES ENCOUNTERED

- Installation of the required local environment e.g. libraries such as TensorFlow
- Issues with array types between libraries Occurred whilst creating a working convolutional neural network using tutorials
- Trying to save, use and classify the input image whilst designing the web application



HOW TO IMPROVE

- Research further ML techniques to improve the model's performance (increase accuracy)
- Significantly altering the CNN architecture and more of its parameters
- Investigate segmenting red blood cells from thin blood smears, allowing the whole classification process to be automated



THANK YOU, I HOPE YOU ENJOYED!

ANY QUESTIONS?

REFERENCES

- [1] WHO, "World Malaria Report 2020," 30 November 2020. [Online]. Available: https://www.who.int/publications/i/item/9789240015791.
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- [9] E. Dauria, "Accuracy, Recall & Precision," 8 December 2019. [Online]. Available: https://medium.com/@erika.dauria/accuracy-recall-precision-80a5b6cbd28d.