Malaria detection through blood cell images analysis using deep learning

## Agenda

- \* Motivation
- \* The Data
- \* Data Preprocessing
- \* Modeling
- \* Conclusion

## Motivation

\* Malaria cases must be recognized promptly in order to treat the patient in time and to prevent further spread of infection in the neighborhood via local mosquitoes. Malaria is considered a potential medical emergency and should be treated accordingly.

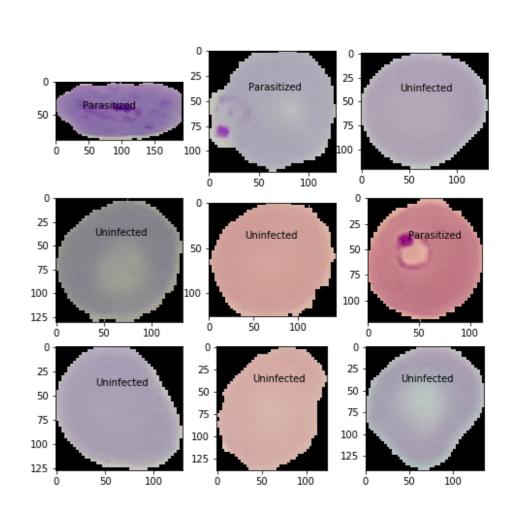
\* Delay in diagnosis and treatment is a leading cause of death in malaria patients. Approximately 400, 000 deaths every year world wide which is mostly affecting poor areas.

## Motivation

- \* The way malaria is diagnosed is a bit tricky as it requires both clinical diagnosis and microscopic diagnosis. Clinical diagnosis phase involves checking patient's symptoms such as fever, chills, sweats, muscle pains, etc.
- \* Microscopic diagnosis is examining patient's blood sample under the microscope to identify parasites.
- \* Building up a model to help diagnosing malaria cases can help automating the process and clinicians so that they can spend more time on treating patients.

## The Data

- \* The dataset used in this project is obtained from the U.S. National Library of Medicine, which is set of blood smear images collected by researchers.
- \* The images were manually annotated by experts at the Mahidol-Oxford Tropical Medicine Research Unit in Bangkok, Thailand.
- \* The dataset contains a total of 27,558 cell images with almost equal instances of parasitized and uninfected cells.



Raw cell images data

## Data Pre-Processing

- \* In order to feed image data to machine learning models we use a few preprocessing methods such as scaling, resizing, transforming, rotating and shifting. The figure below show raw image samples before preprocessing.
- \* Dataset is downloaded from NIH website in CSV format which includes labeled cell images. We first write a source code to divide dataset into three sets those are training, validation and test sets.
- \* Training set contains 80 % of the whole data while test and validation sets are sharing 10 % respectively. After splitting dataset, we seek for the best size to resize images so that our algorithm would work at optimum pace

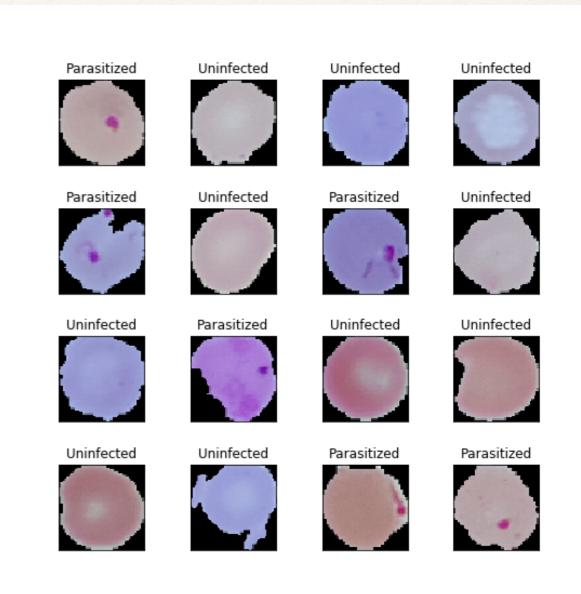
## Data Pre-Processing

- \* Average pixel dimension was obtained as [133.16, 132.61, 3], while median pixel dimension was [130, 130, 3].
- \* However, since we ran our models on a CPU, we picked even smaller dimensions as such [64, 64, 3] to save time on modeling phase.

	SampleSize	Height	Width	ColorChannel
TrainData	22235	64	64	3
Validation	2470	64	64	3
Test	6177	64	64	3

## Data Pre-Processing

\* The figure illustrates the blood smear images after resizing process. We will also apply transformation, rotation and shifting techniques later in modeling section using Keras data augmentation methods.



# Modeling

- \* What we expect from machine learning algorithm is to detect blood cell images with parasitizes which can be seen as red dot by a microscope after sample is stained with a contrasting agent to help highlight malaria parasites in the blood cell.
- \* If that is manually done by a clinician, it would take a lot of time to count all.
- \* There is actually a web application developed by Dr. Carlos Atico Ariza which uses deep learning behind the scenes that screens and diagnose Malaria.

# Modeling

- \* We picked our baseline model as K Nearest Neighbors (KNN) model to start off modeling.
- \* Then Simple Neural Network with two hidden dense layers tested out.
- Next, Convolution Neural Network built from scratch with getting help of my mentor.
- \* Finally, the ResNet model is tested out after a few manipulation from its original version on Adrian's blogpost.

# Modeling

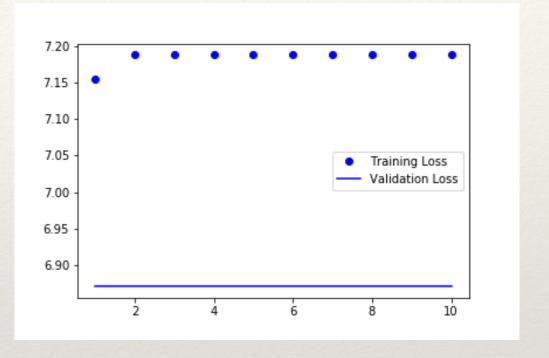
#### KNN

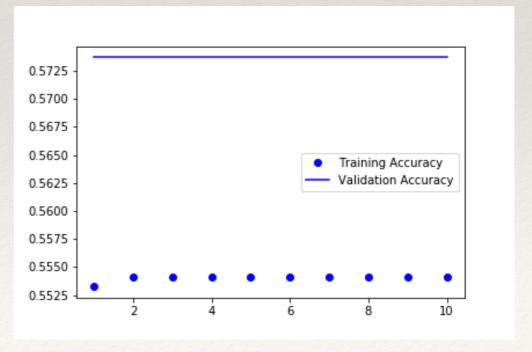
- \* We have got 59 % accuracy score with KNN which is not too bad even with this not learning method, given that the probability of randomly guessing the correct class is 50 %.
- \* KNN model correctly classified parasitized blood cells 51 % of the time.
- \* Looks like KNN did a better job on classifying `uninfected` class based on the Precision score. Apparently, some `uninfected` cells classified as `infected` (False Positive) as we can see from Precision score of `infected` class.

# Modeling

#### Simple Neural Network

\* The model used here consists of a sequence of two hidden densely connected layers having 768 and 384 nodes in each respectively to classify our images. After 5 iteration, trained model has reached about 56 % accuracy which is not really useful.





# Modeling

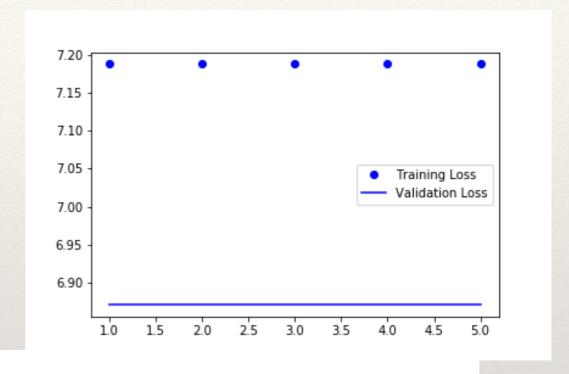
#### **Conv Neural Network**

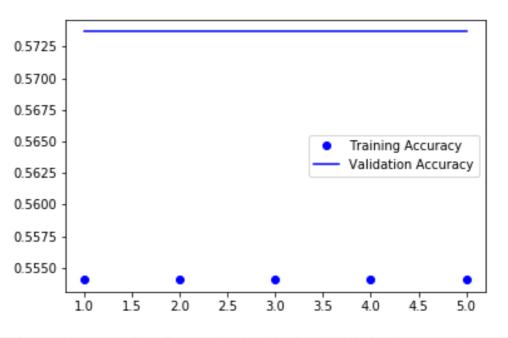
- \* Conv2D are convolution layers that will deal with our input images, which are seen as 2-dimensional matrices.
- \* In our CNN model kernel size is defined as (3, 3) matrix which is a filter matrix used for blurring, sharpening, embossing, edge detection and more by visiting every pixels in image.
- \* We also use dropout to regularize and reduce unnecessary feature dependencies in our network. It helps reducing over-fitting and generalization of the model.

## Modeling

#### **Conv Neural Network**

- \* Max pooling is a downsampling technique used to reduce the amount of parameters and computation in network and to control over-fitting.
- We used most common size of (2, 2) pooling layer here in the model.





# Modeling

#### Residual Neural Network (ResNet)

Here is some details about the data preprocessing before feeding data into ResNet model:

- \* Batch Size 128,
- \* 5 Epochs which took 2 hours to complete with CPU,
- \* 0.1 learning rate,
- \* (64, 64, 3) image size and
- \* also data augmentation technique of Keras is implemented for each dataset.

# Modeling

#### Residual Neural Network (ResNet)

- \* ResNet will then perform (3, 4, 6) stacking with (64, 128, 256, 512) CONV layers where the first 64 filters will be applied before reducing spatial dimension.
- \* Next, 3 sets of residual modules that will be learning 32, 32 and 128 CONV filters will be stacked.
- \* Followed by reducing the spatial dimensions and stack 4 sets of modules where each CONV layers will learn 64, 64 and 256 filters.
- \* Finally, we stack 6 sets of residual modules where again each CONV layers learns 128, 128 and 512 filters.

# Modeling

#### Residual Neural Network (ResNet)

- \* There is substantial improvement on results compared to KNN, which was our baseline model.
- \* Infected class was caught with 98% precision and 94% recall while the geometric mean of them f1 score is 96%. So the ResNet model is almost perfect with a little FP and FN values.
- \* High precision scores indicates that there is almost no blood cells that were healthy and classified as infected.
- \* Training accuracy of model as mentioned is about 96% and validation accuracy is about 95%.

## Modeling

Here is the overall comparison table of model accuracies below.

Model Name	Validation Accuracy		
KNN	59%		
Simple NN	58%		
CNN	58%		
ResNet	96%		

## Thank You