Project 2: Malaria Dectection on Cell Images (Transfer Learning)

ECE 595

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*: (Based on the previous work of Barath Narayanan Narayanan, Redha Alia, Russell C. Hardie)

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Note: Any steps directly repeated from the CNN Architecture are fully explained and covered in the CNN Architecture live script.

```
% Images datapath - Please modify your path accordingly
datapath='D:\Connor\ECE 595\Project 2\cell_images\cell_images';

% Image datastore
img_datastore = imageDatastore(datapath, ...
'IncludeSubfolders',true, ...
'LabelSource','foldernames');

% Determine amount of each label
total_split = countEachLabel(img_datastore)
```

total_split = 2×2 table

	Label	Count
1	Parasitized	13779
2	Uninfected	13779

```
% Store labels in a variable
labels = img_datastore.Labels;

% Can use built in methods that are part of Deep Learning toolbox and discussed in
paper

% Split the data into training and testing datasets
```

```
train_percent = 0.8;
[img_train,img_test] = splitEachLabel(img_datastore, train_percent, 'randomize');

% Further split the training dataset in half to form the validation dataset
valid_percent = 0.1;
[img_valid, img_train] = splitEachLabel(img_train, valid_percent, 'randomize');

train_split=countEachLabel(img_train);

% Visualize part of the dataset to ensure correctly loaded

num_images = length(img_datastore.Labels);
```

Note: As the same dataset is loaded and the same preprocessing function and data augmentation are applied to this data, there is no need to visualize the images again. For data visulization, please see the CNN Architecture live script.

Transfer Learning Approach without Preprocessing

In place of constructing a CNN fully from scratch, an existing and well-tested architecture is loaded and its layers are modified to better fit this classification problem. 'ResNet50' is chosen for this classification task over VGG16 and Inceptionv3 for two major reasons. First of all, it has a far fewer number of parameters than VGG16 at around 25 million compared to VGG16's ~138 million. Secondly, although Inceptionv3 has a similar amount of parameters to ResNet50 and can run multiple operations in parallel, it is better suited for recognizing many features from multiple perspectives and is much more complex to modify.

For these reasons, ResNet50 is chosen for this classification task.

```
% Load ResNet50
net = resnet50;

% Parameter to define the number of units in the new fc layer -
% 'numClasses' is equal to 2 in this case as there are two types of labels
numClasses = numel(categories(img_train.Labels));

% Define layer graph
lgraph = layerGraph(net);

% Clear the existing resnet architecture
clear net;


% Define new layers

% Ref: (https://www.mathworks.com/matlabcentral/answers/398045-can-someone-explain-
to-me-the-meaning-of-these-numbers-is-this-line-of-code)
% 'WeightLearnRateFactor' is the factor by which the learning rate is
% scaled for the weights in this layer compared to the global learning rate
```

```
% 'BiasLearnRateFactor' is a similar factor that scales the learning
% rate, except for the biases in this layer.

new_fc = fullyConnectedLayer(numClasses, ...
    'Name', 'custom_fc', ...
    'WeightLearnRateFactor', 8, ...
    'BiasLearnRateFactor', 8);

new_softmax = softmaxLayer('Name', 'custom_softmax');
new_classification = classificationLayer('Name', 'custom_classification');


% Replace the last three layers with new layers using replaceLayer()
% function
lgraph = replaceLayer(lgraph, 'fc1000', new_fc);
lgraph = replaceLayer(lgraph, 'fc1000_softmax', new_softmax);
lgraph = replaceLayer(lgraph, 'ClassificationLayer_fc1000', new_classification);

% Resize all training/validation/test images to [224 224] for ResNet
% architecture
img_train.ReadFcn=@(filename)reshape_image(filename, [224 224]);
img_valid.ReadFcn=@(filename)reshape_image(filename, [224 224]);
img_test.ReadFcn=@(filename)reshape_image(filename, [224 224]);
```

In the above code, the last three layers of ResNet50: a fullyConnectedLayer with 1000 units, softmaxLayer, and classificationLayer, are removed and replaced by new different fullyConnectedLayer and the same softmaxLayer and classificationLayer. The number of hidden units is dropped from 1000 to 2 as the output of the last fullyConnectedLayer must match the number of classes. The learning rate factors for the weights and biases are increased twentyfold in this layer to compensate for removing 99.8% of the weights in the layer.

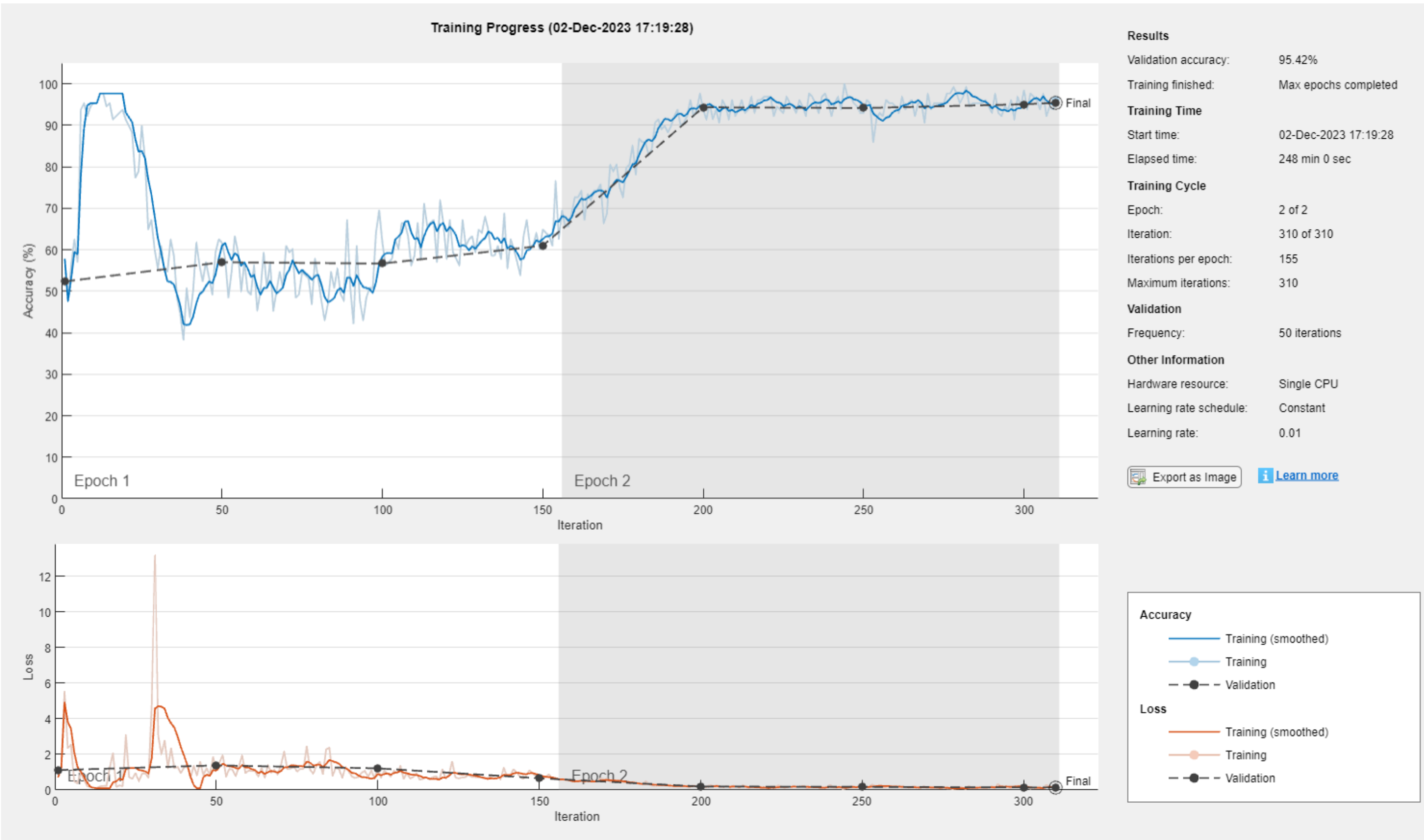
Training

To keep a level of consistency, the training hyperparameters are kept the same between training on the different networks, except the number of epochs is reduced to 2 to save on training time.

```
options = trainingOptions('sgdm','MaxEpochs', 2, 'MiniBatchSize', 128, ...
    'ValidationData', img_valid, ...
    'Shuffle', 'every-epoch', ...
    'ValidationFrequency', 50, ...
    'Plots', 'training-progress', ...
    'ValidationPatience', 4);

% Train the Network
netTransfer = trainNetwork(img_train, lgraph, options);
```

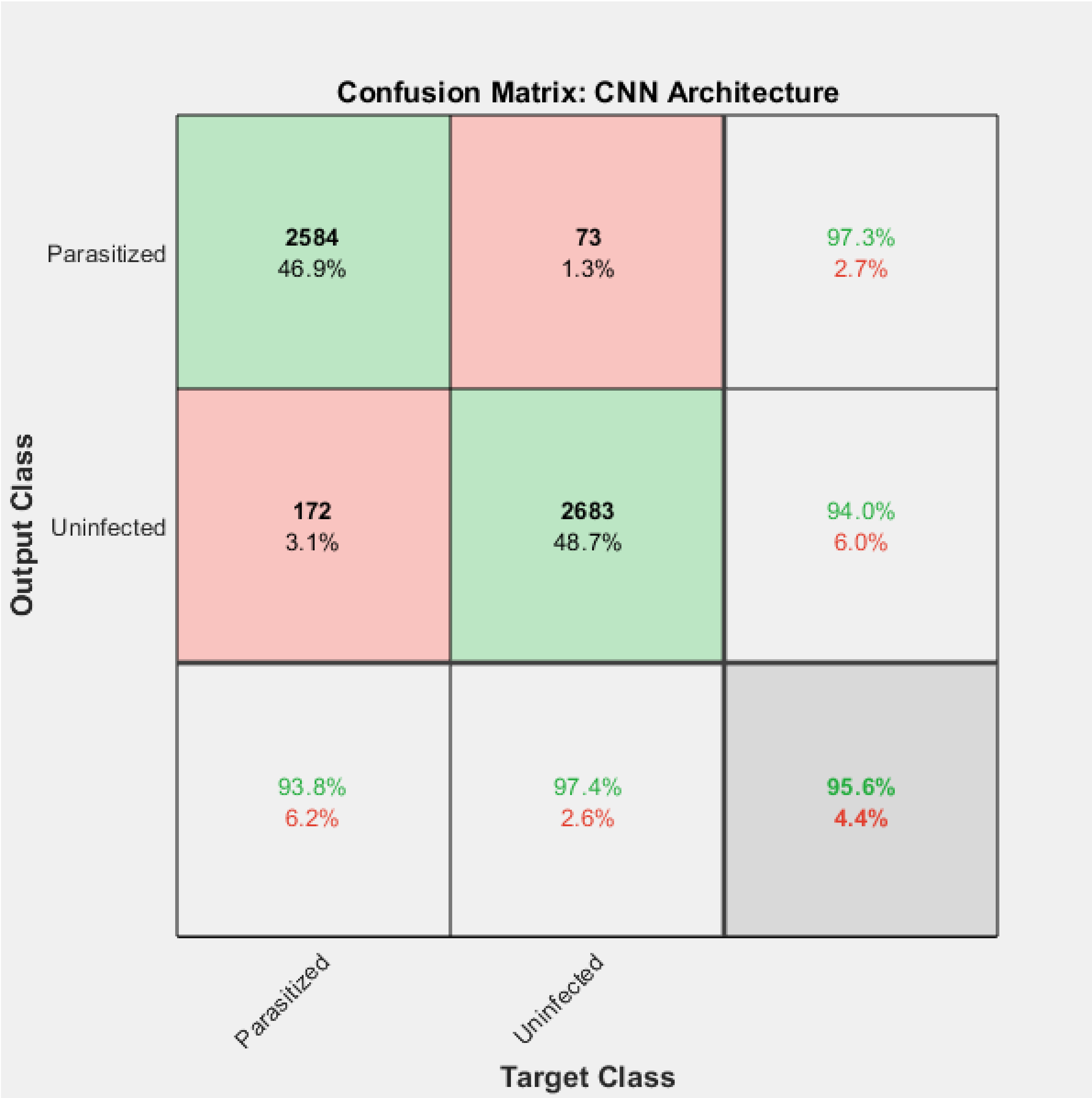
```
Training on single CPU.
Initializing input data normalization.
|==================================================================================================================
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learni
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate
|==================================================================================================================
|       1 |           1 |       00:03:24 |       57.81% |       52.36% |       0.7093 |       1.1207 |          0.0
```

```
|       1 |        50 |     00:29:05 |      61.72% |      56.99% |      1.1351 |      1.3843 |      0.01
|       1 |       100 |     00:54:15 |      61.72% |      56.67% |      1.2119 |      1.2185 |      0.01
|       1 |       150 |     01:36:36 |      64.84% |      60.98% |      0.7260 |      0.6626 |      0.01
|       2 |       200 |     02:21:16 |      93.75% |      94.33% |      0.1854 |      0.1965 |      0.01
|       2 |       250 |     03:08:01 |      92.97% |      94.15% |      0.1857 |      0.1775 |      0.01
|       2 |       300 |     03:54:47 |      98.44% |      95.05% |      0.0752 |      0.1475 |      0.01
|       2 |       310 |     04:05:25 |      96.09% |      95.42% |      0.1453 |      0.1350 |      0.01
|==========================================================================================================
Training finished: Max epochs completed.
```

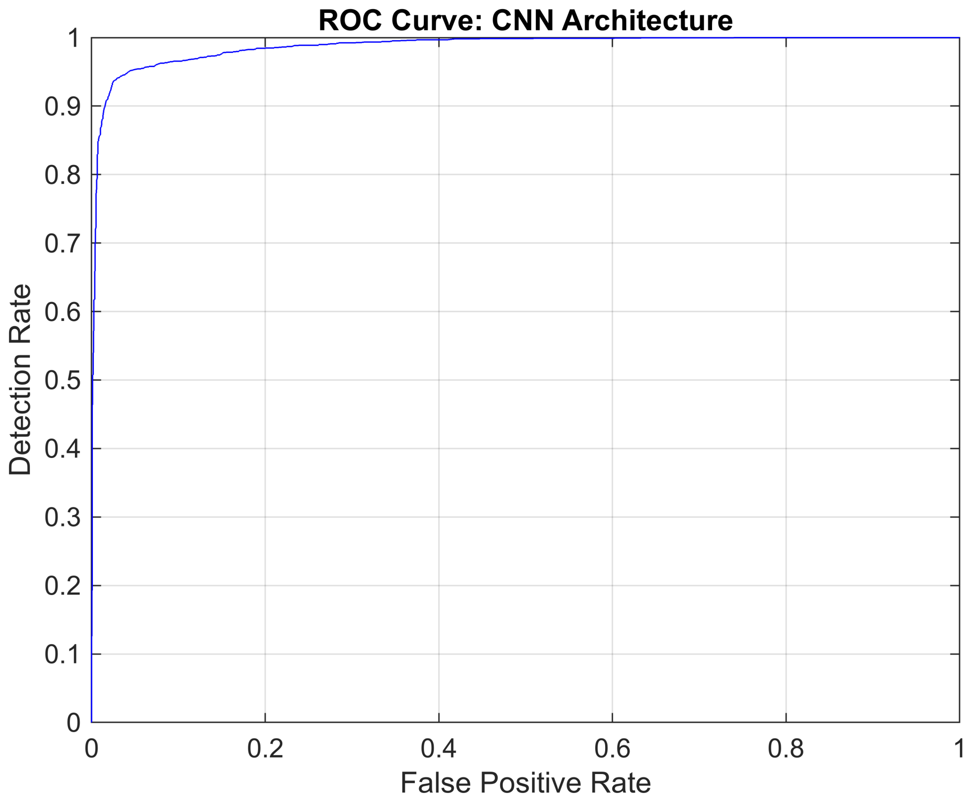


Testing

```
% Predict Test Labels using classify command
[predicted_labels, posterior] = classify(netTransfer, img_test);

% Actual Labels
actual_labels = img_test.Labels;

% Confusion Matrix
figure;
plotconfusion(actual_labels, predicted_labels)
title('Confusion Matrix: CNN Architecture');
```




```
test_labels = double(nominal(img_test.Labels));

% ROC Curve - Our target class is the first class in this scenario.
[fp_rate, tp_rate, T, AUC] = perfcurve(test_labels, posterior(:,1),1);
figure;
plot(fp_rate,tp_rate,'b-');hold on;
grid on;
title('ROC Curve: CNN Architecture')
xlabel('False Positive Rate');
ylabel('Detection Rate');
```




```
% Area under the ROC value
AUC
```

```
AUC = single

    0.9876
```

Transfer Learning Approach with Preprocessing

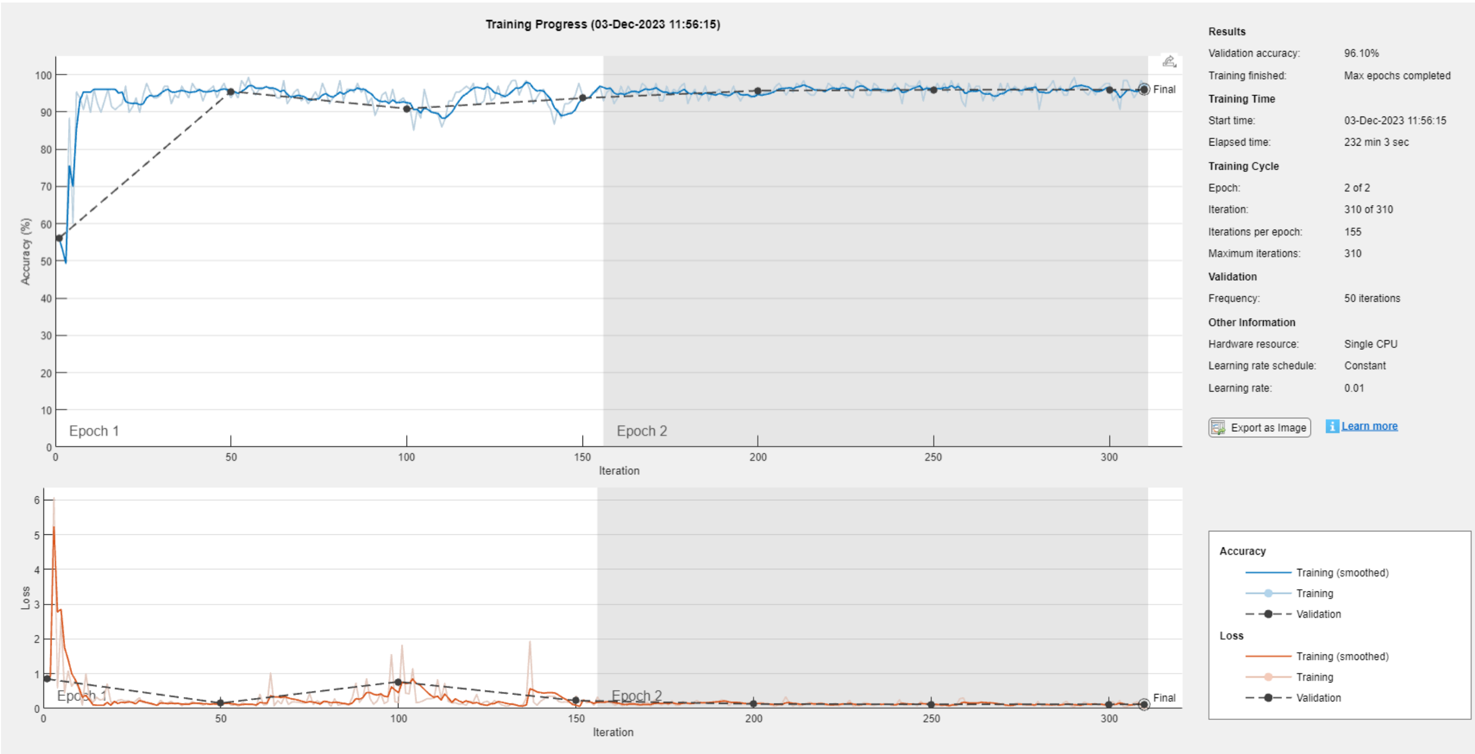
```
% Utilize recommended augmentedImageDatastore for faster
% resizing/transforming whilst preprocessing
img_train.ReadFcn=@(filename)preprocess_malaria_images(filename, [224, 224]);
img_valid.ReadFcn=@(filename)preprocess_malaria_images(filename, [224, 224]);
```

Training

```
% Train the Preprocessed Network
netTransfer_preprocessed = trainNetwork(img_train, lgraph, options);
```

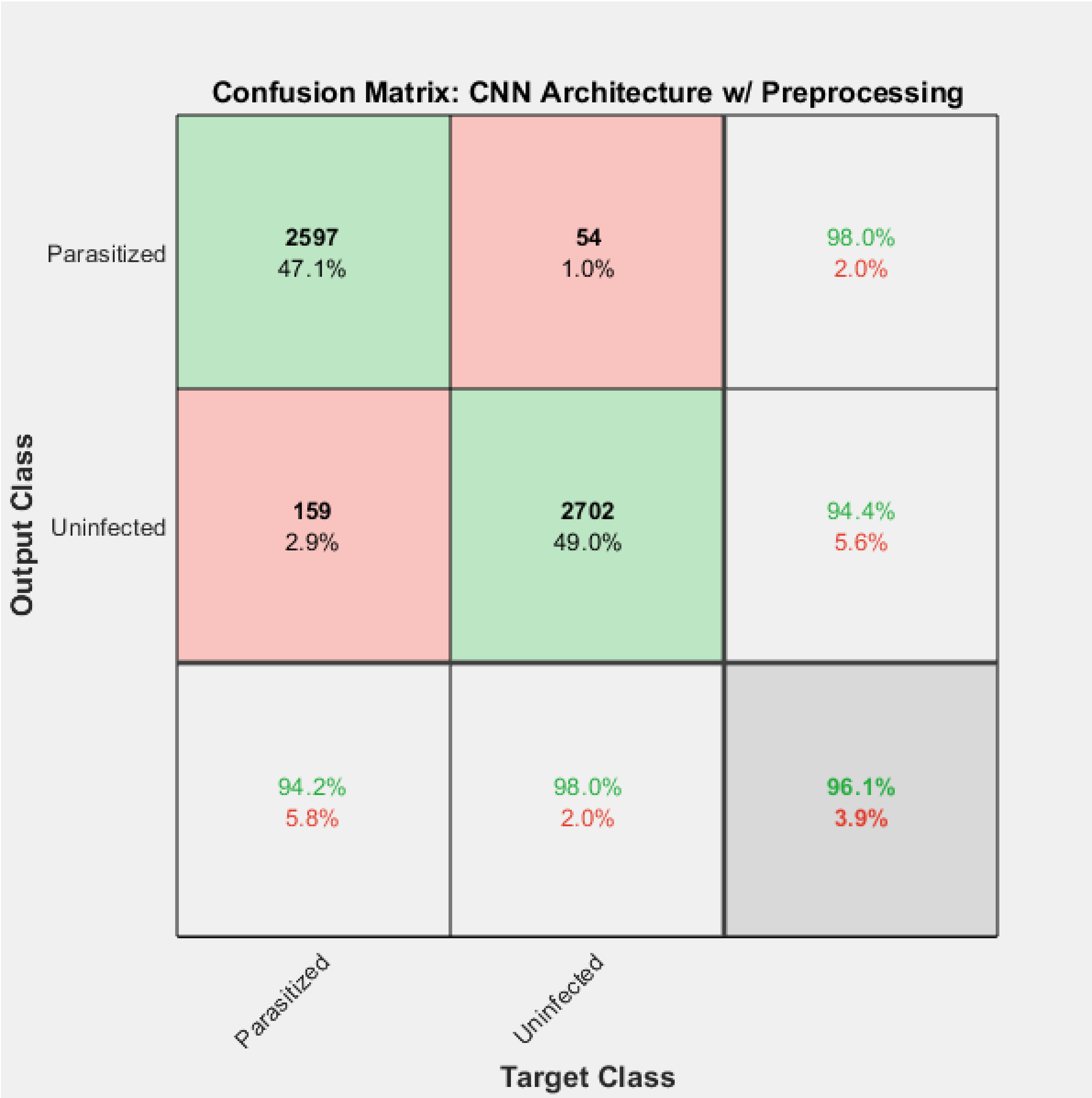
```
Training on single CPU.
Initializing input data normalization.
|=========================================================================================================================
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learni
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate
|=========================================================================================================================
|       1 |           1 |       00:03:40 |       56.25% |       56.03% |       0.7554 |       0.8494 |          0.0
|       1 |          50 |       00:36:39 |       93.75% |       95.51% |       0.1762 |       0.1555 |          0.0
|       1 |         100 |       01:07:03 |       92.19% |       90.88% |       0.1720 |       0.7683 |          0.0
```

```
|       1 |         150 |       01:40:53 |       94.53% |       93.69% |       0.3607 |       0.2263 |       0.0
|       2 |         200 |       02:19:37 |       96.09% |       95.69% |       0.1822 |       0.1297 |       0.0
|       2 |         250 |       02:57:08 |       95.31% |       95.92% |       0.1220 |       0.1194 |       0.0
|       2 |         300 |       03:36:03 |       97.66% |       95.96% |       0.0691 |       0.1213 |       0.0
|       2 |         310 |       03:49:06 |       96.88% |       95.96% |       0.0885 |       0.1176 |       0.0
|==========================================================================================================
Training finished: Max epochs completed.
```

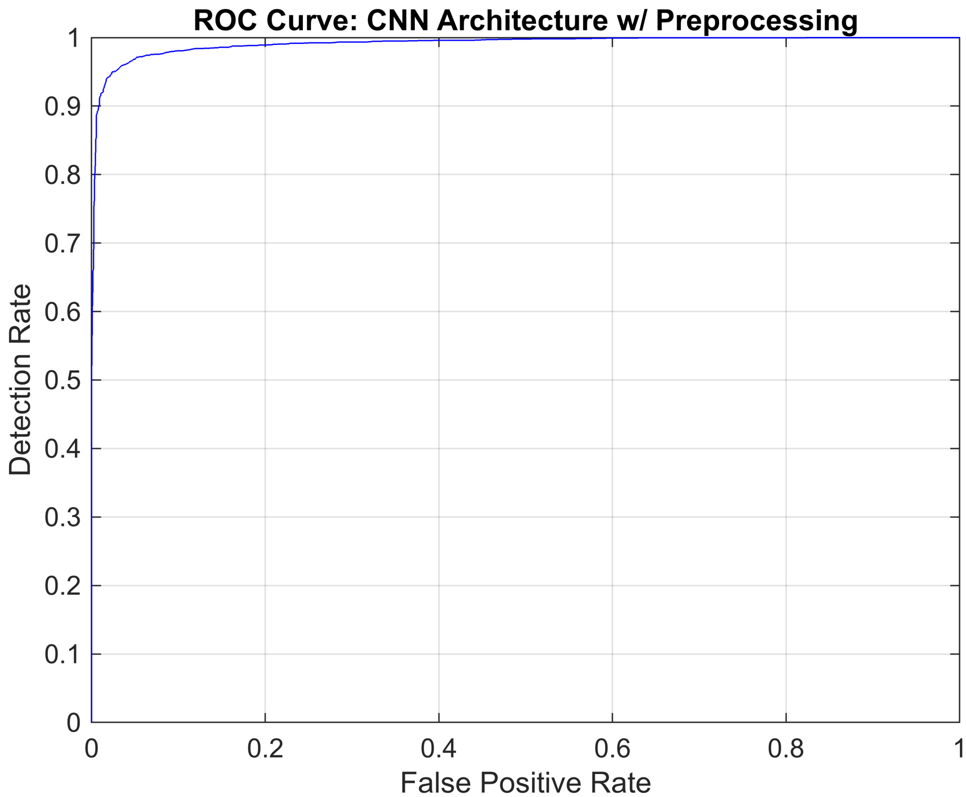


Testing

```
% Preprocess the test cases similar to the training
img_test.ReadFcn=@(filename)preprocess_malaria_images(filename, [224, 224]);

% Predict Test Labels using classify command
[predicted_labels, posterior] = classify(netTransfer_preprocessed, img_test);

% Confusion Matrix
figure;
plotconfusion(actual_labels, predicted_labels)
title('Confusion Matrix: CNN Architecture w/ Preprocessing');
```




```
% ROC Curve - Our target class is the first class in this scenario.
[fp_rate, tp_rate, T, AUC] = perfcurve(test_labels, posterior(:,1),1);
figure;
plot(fp_rate,tp_rate,'b-');hold on;
grid on;
title('ROC Curve: CNN Architecture w/ Preprocessing')
xlabel('False Positive Rate');
ylabel('Detection Rate');
```




```
% Area under the ROC value
AUC
```

```
AUC = single

    0.9915
```

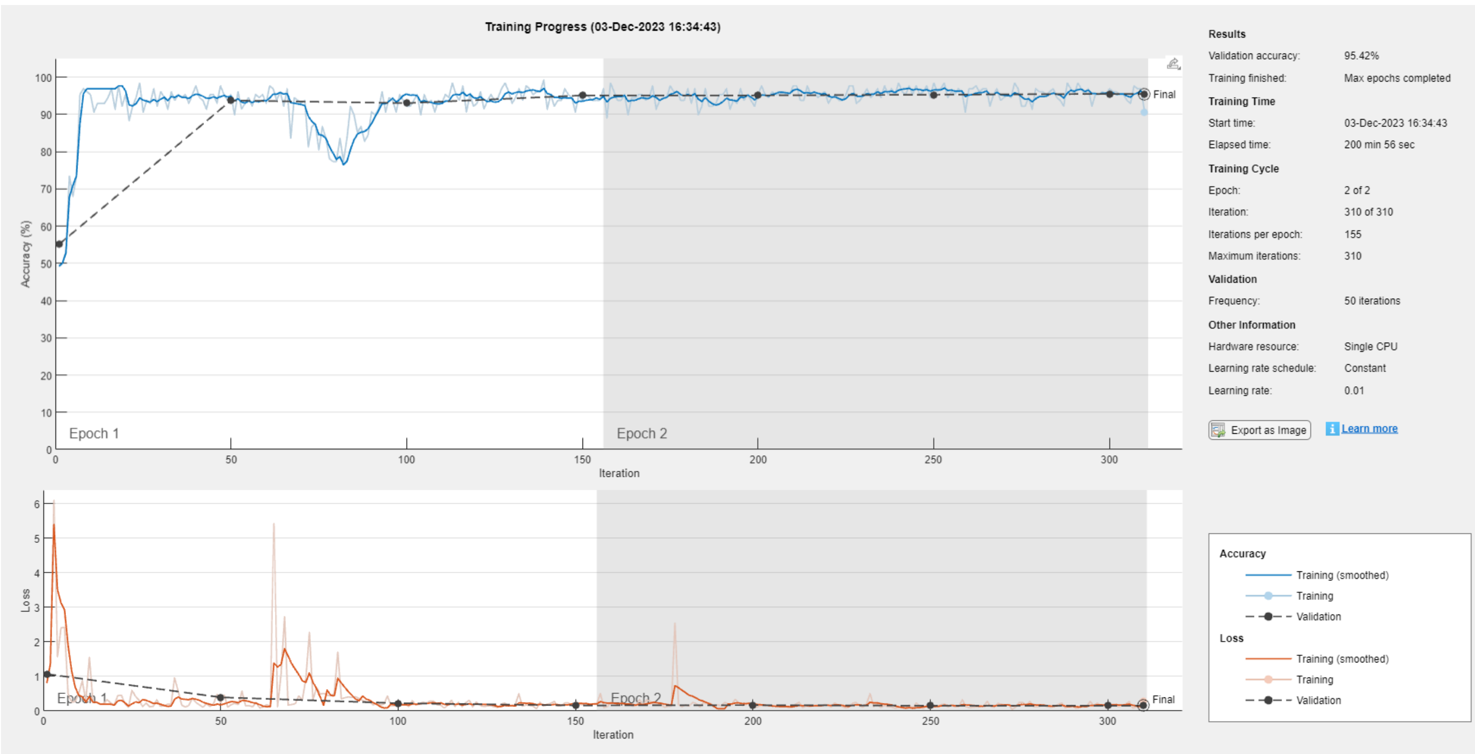
Transfer Learning Approach with Preprocessing and Data Augmentation

```
% Data Augmentation (Ref: https://www.mathworks.com/help/deeplearning/ref/
imagedataaugmenter.html)

% Configure a set of preprocessing options for image augmentation
% 'RandRotation': Rotates the image anywhere between -90 and 90 degrees
% 'RandXReflection': 50 % chance of flipping the image about the x-axis
% 'RandYReflection': 50 % chance of flipping the image about the y-axis
image_augumenter=imageDataAugmenter('RandRotation', [-90 90], 'RandXReflection',
true,'RandYReflection', true);

aug_img_train_datastore = augmentedImageDatastore([224 224],
img_train,'DataAugmentation', image_augumenter);
aug_img_valid_datastore = augmentedImageDatastore([224 224],
img_valid,'DataAugmentation', image_augumenter);
```

Training

```
% Train the Preprocessed and Augmented Network
netTransfer_preprocessed_augmented = trainNetwork(aug_img_train_datastore, lgraph,
options);
```

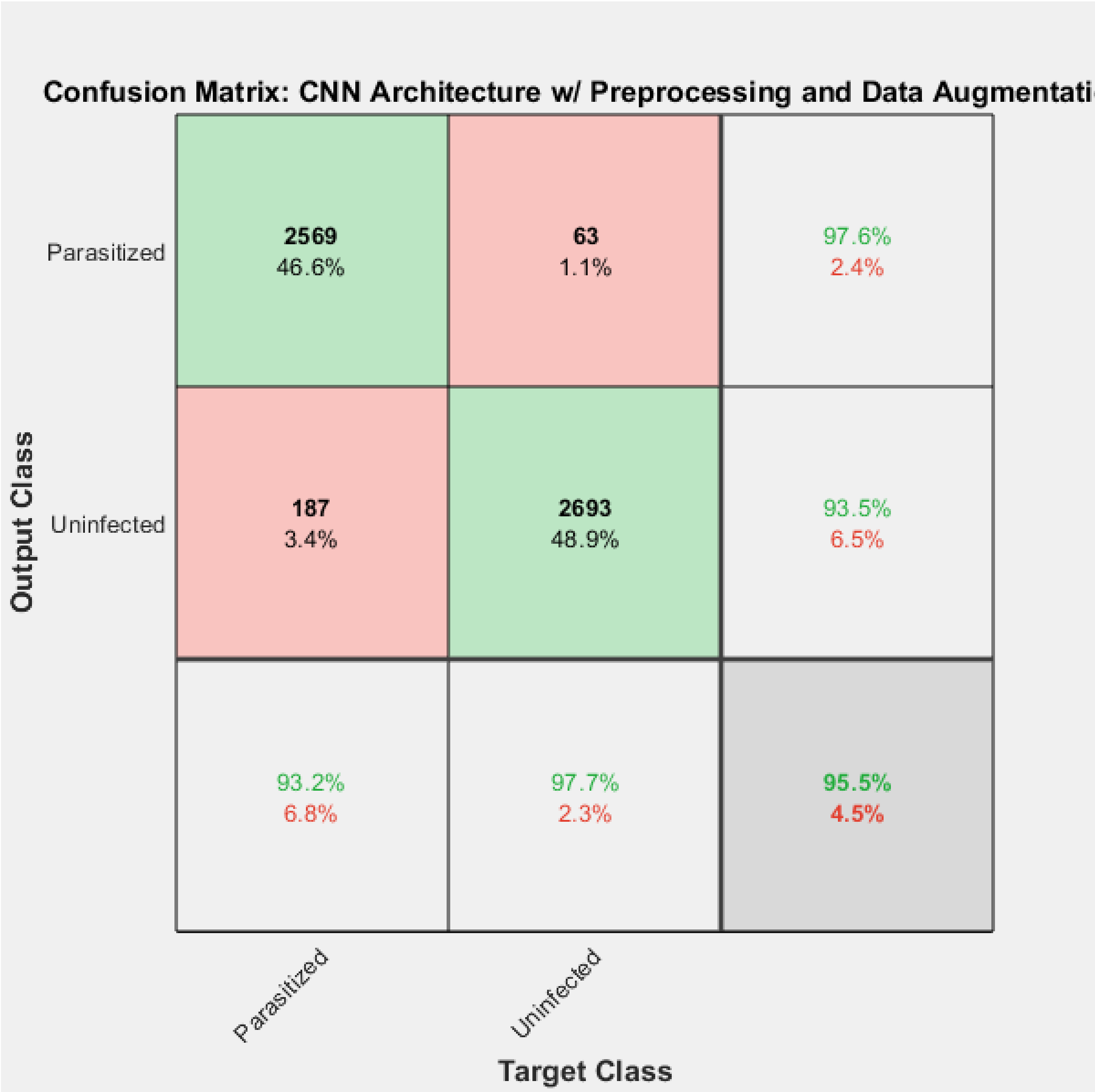
```
Training on single CPU.
Initializing input data normalization.
|========================================================================================================
|  Epoch  |  Iteration  |  Time Elapsed  |  Mini-batch  |  Validation  |  Mini-batch  |  Validation  |  Base Learni
|         |             |   (hh:mm:ss)   |   Accuracy   |   Accuracy   |     Loss     |     Loss     |      Rate
|========================================================================================================
|       1 |           1 |       00:03:53 |       49.22% |       55.08% |       0.8101 |       1.0703 |          0.01
|       1 |          50 |       00:36:21 |       95.31% |       93.74% |       0.2327 |       0.3966 |          0.01
|       1 |         100 |       01:08:19 |       92.19% |       93.01% |       0.2664 |       0.2246 |          0.01
|       1 |         150 |       01:37:15 |       93.75% |       95.10% |       0.2592 |       0.1607 |          0.01
|       2 |         200 |       02:08:05 |       95.31% |       95.10% |       0.1837 |       0.1694 |          0.01
|       2 |         250 |       02:38:00 |       98.44% |       95.28% |       0.0666 |       0.1534 |          0.01
|       2 |         300 |       03:10:33 |       96.88% |       95.51% |       0.1281 |       0.1530 |          0.01
|       2 |         310 |       03:18:56 |       90.62% |       95.51% |       0.2792 |       0.1519 |          0.01
|========================================================================================================
Training finished: Max epochs completed.
```



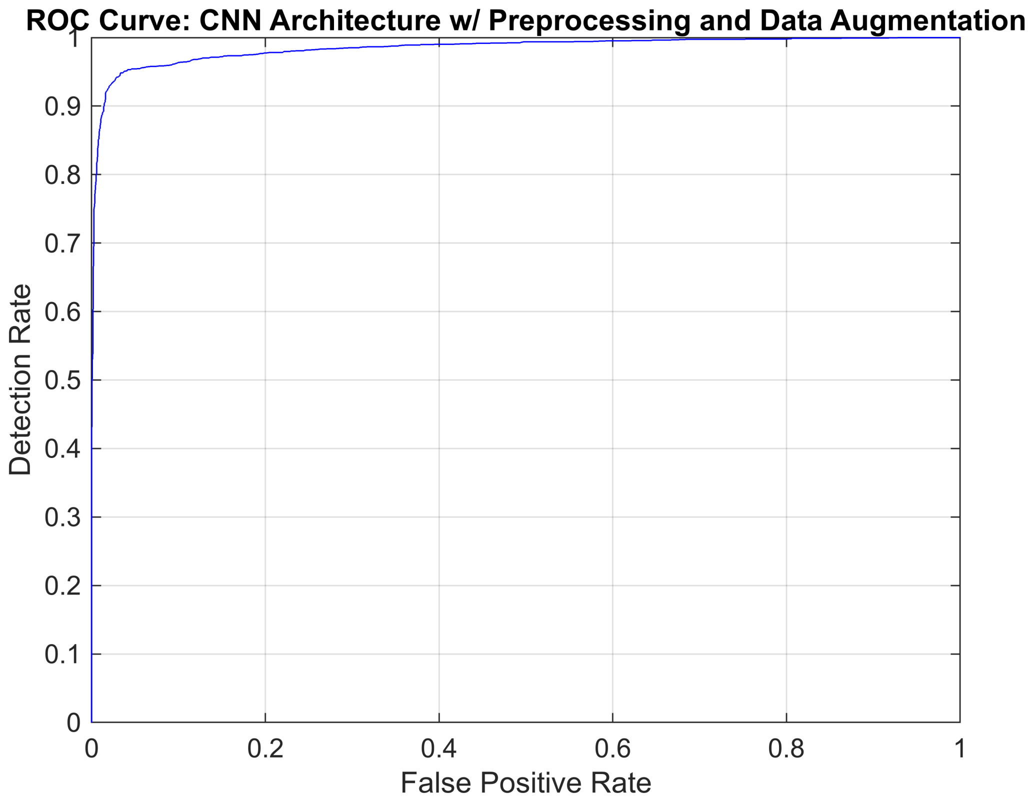
Testing

```
% Augment the test cases similar to the training
aug_img_test_datastore = augmentedImageDatastore([224 224],
img_test,'DataAugmentation', image_augumenter);

% Predict Test Labels using classify command
[predicted_labels, posterior] = classify(netTransfer_preprocessed_augmented,
img_test);

% Confusion Matrix
figure;
```

```
plotconfusion(actual_labels, predicted_labels)
title('Confusion Matrix: CNN Architecture w/ Preprocessing and Data Augmentation');
```




```
% ROC Curve - Our target class is the first class in this scenario.
[fp_rate, tp_rate, T, AUC] = perfcurve(test_labels, posterior(:,1),1);
figure;
plot(fp_rate,tp_rate,'b-');hold on;
grid on;
title('ROC Curve: CNN Architecture w/ Preprocessing and Data Augmentation')
xlabel('False Positive Rate');
ylabel('Detection Rate');
```




```
% Area under the ROC value
AUC
```

```
AUC = single

    0.9848
```

Results & Suggestions for Improvement

Data	Final Training Accuracy	Final Validation Accuracy	Test Accuracy	AUC	# of Epochs	Total Training Time
No Preprocessing	95.31%	95.96%	96.7%	0.9924	2	04:05:25
Preprocessing	95.31%	95.78%	96.3%	0.9899	2	00:17:01
Preprocessing and Data Augmentation	96.88%	95.60%	96.0%	0.9891	7	00:53:24

Note: Although the number of epochs the network was set to run for was 8 in all 3 cases, the training would always finish after having 'Met validation criterion', irregardless of what epoch it was currently on or the total time spent training. This is why the network finished training after 3 and 7 epochs for the preprocessed and preprocessed and augmented datsets respectively.

All three types of input data achieved a respectable 95 - 97% accuracy on each indivial subset. The very slight drop in validation and test accuracy and identical training accuracy after going from no preprocessing to preprocessing reveals that a better preprocessing function could have been chosen. However, the preprocessed data was able to achieve this similar accuracy in significantly less training time.

Also notable is the ~1.5% jump in training accuracy for the preproccesed and augmented data. Despite this increase, the preprocessed and augmented data still had the lowest validation and test accuracy. This is indicative of overfitting on the training data, which is further supported by the preprocessed and augmented data having the lowest AUC. This overfitting could be combatted by decreasing the number of fullyConnected layers and/or increasing the dropout within the CNN.

Reshape Function

```
function [Iout] = reshape_image(filename,image_size)
% This function resizes all images to a fixed size
%
% Author: Barath Narayanan
% Date: 11/16/2021
%

% Read the images
I=imread(filename);

% Output Image
Iout=imresize(I,image_size);

end
```

Preprocessing Function

```
function I_adapthisteq = preprocess_malaria_images(filename, desired_size)

% This function preprocesses malaria images using contrast enhancement and
% resizes the image
% Author: Connor Prikkel
% Ref: https://www.mathworks.com/help/images/contrast-enhancement-techniques.html

% Read the Image
I = imread(filename);

% Some images might be grayscale, replicate the image 3 times to
% create an RGB image.

if ismatrix(I)
  I = cat(3,I,I,I);
end

% Convert the image from RGB color space to L*a*b* color space
I_lab = rgb2lab(I);
```

```
% Values of luminosity span a range from 0 to 100
% Scale values to range [0 1]
max_luminosity = 100;
L = I_lab(:,:,1)/max_luminosity;


% Contrast-Limited Adaptive Histogram Equalization - operates on small
% sections of the intensity image at a time
I_adapthisteq = I_lab;
I_adapthisteq(:,:,1) = adapthisteq(L)*max_luminosity;
I_adapthisteq = lab2rgb(I_adapthisteq);

% Resize the image
I_adapthisteq = imresize(I_adapthisteq, [desired_size(1) desired_size(2)]);

end
```