Deep Learning for Malaria Detection

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1 Executive Summary

Key take-aways for Malaria detection from the deployment of CNN models proffers the real likelihood of speeding up diagnosis of Malaria of infected patients. The inclusion of more layers appears to improve model predictions, compare model-1 with the other models. Model-1 delivers 98% accuracy and F1-score with eight false negatives and 38 false positives, see Fig. 1. The CNN models indicate that image augmentation is critical to leverage accurate predictions, yet blurring, for example, does not clarify infected versus parasitized red blood cells (RBC). Rather, (next steps) perhaps sharpening the images of infected RBC, providing edge enhancement, could improve image classification for a CNN model. Furthermore, considering the pixel data per image, looking at the distributions of pixel data between infected and uninfected may also provide a feature to distinguish Malaria positive patients. Hence, since each image would show large peaks in the pixel distribution for the infected RBCs, then analyzing this as a statistical distribution could be potentially important.

2 Problem and Solution Summary

Blood-borne infectious diseases effect all populations across the globe. Mosquito-borne transmitted diseases, in particular, are wide-spread and given their fomite inhabits coastal or water-rich areas alongside large populations presents a danger to the health of the public. Malaria is a mosquito-borne infectious disease that affects millions of people each year. In a given year, nearly 400K patients die resulting from

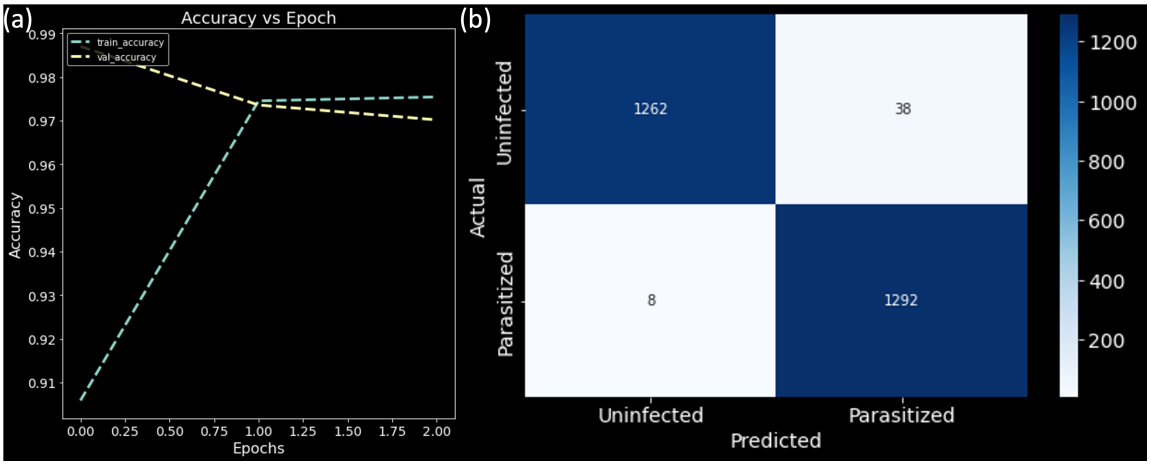


Figure 1: The optimal model CNN for Malaria detection. (a) Model 1 accuracy, and (b) confusion matrix.

complications of the illness. People infected by Malaria are bitten by an Anopheles mosquito carrying the *Plasmodium parasite*. The presence of these parasites can be found in RBC, where the parasite multiplies and disrupts normal cellular function. Below is an electron-micrograph of an infected RBC, Fig. 2.

2.1 Objective

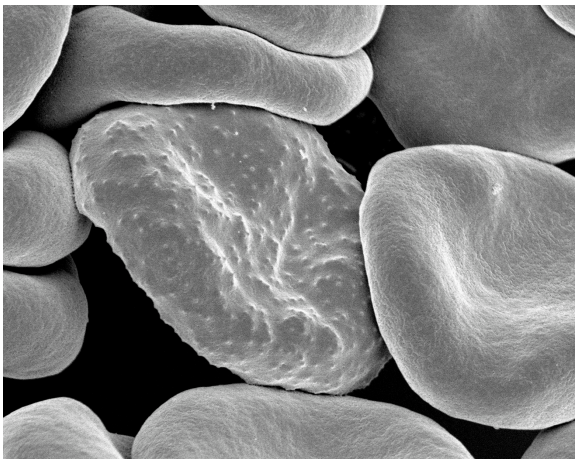
The objective is develop and deep learning approach, computer vision model, that analyzes a large dataset of images of RBCs and detects the presence of Plasmodium parasite. The dataset is comprised of infected (**parasitized**) and uninfected images, Fig. 3. There are a total of 24,958 train and 2,600 test images (colored).

2.2 Convolutional Neural Networks – Models

Convolutional neural networks (CNN) provide an excellent artificial intelligence technique for image processing and image classification, see Fig. 4. From Fig. 4, we can see the architecture of a CNN, where the advantage of CNNs concerns the techniques' ability to detect spatial structure. CNNs take pixels from images as inputs and pass

Figure 2: Electron micrograph of malaria infected RBC displaying 'knobs' (protrusions) along the cellular wall.

Wikipedia



them across neurons (perceptron) and provide a prediction. As data forward propagates across the CNN, the features are 'detected', or edges and shapes acquire weights via an activation function, i.e., ReLU, and where a convolution is applied to extract these features for image classification. The size of the image is pooled or reduced in size to increase the speed of image classification. More convolutions (smoothing) can be applied with subsequent pooling, then flattening where a vector is passed for predictions. This process can also undergo ***back propagation***, which the data propagates backward across the neural network. Improved models such as VGG16, see Fig. 5, or ResNet can be employed to tackle transfer learning and possibly improve learning.

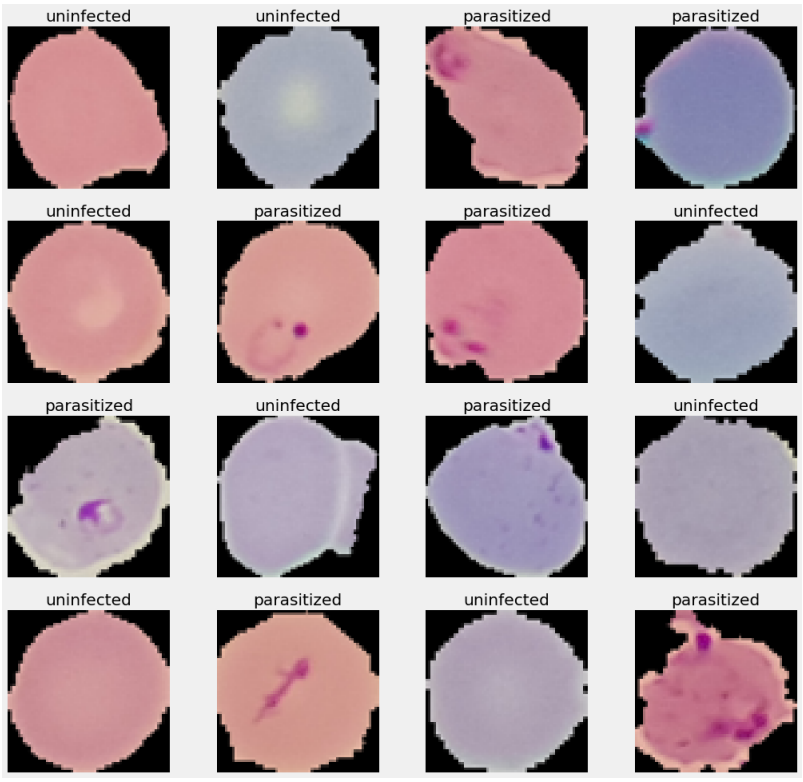


Figure 3: Sample of RBC dataset showing parasitized and uninfected cells.

3 Recommendations for Implementation

What are some key recommendations to implement the solutions?

It is important to note that VGG16 and ResNet models did not improve over Mode-1, compare Fig.1 with Fig. 6. This is likely a result of *user error*. Hence, further analysis of these two models should lead to better transfer learning for Malaria classification. The overall performance for VGG16 and ResNet was also lower compared to Model-1. Moreover, introducing image augmentation would benefit all models. Further, it is advised to apply various image augmentation approaches, such as, scaling, zooming, translation, rotation, and flipping. Image augmentation will add some variability in the images prepping the weights. Furthermore, the introduction of denser layers could also be implemented to enable improved learning; however, this will likely hamper performance and expand the total number of weights to evaluate which could lead to flat gradients (no learning).

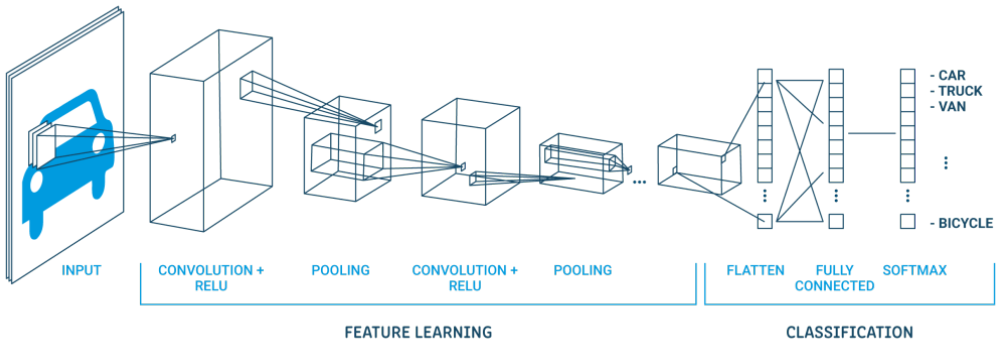


Figure 4: Convolutional Neural Network (CNN) general technique for classifying images. This model provides the basis for computer vision.

What are the key actionables for stakeholders?

Stakeholders should feel confident implementing CNN-models for image classification of Malaria. Model-1, a simpler model, delivers excellent accuracy compared to the other four models. Expanding on this model and coupling it to a linear classifier (simple regression) could further improve its accuracy. The model could also be passed to VGG16 or ResNet, for example, and deliver improved predictions. The model is capable of handling large amounts of data and relieves the need for human evaluation.

What is the expected benefit and/or costs? What are the key risks and challenges?

CNNs provide the added benefit of analyzing in *en masse* huge amounts of data or images of infected erythrocytes. This improves over human evaluation of pathological samples in volume. However, a key risk is the predictions of both false positive and false negatives. This challenges the deployment of Model-1. Although the CNN does not deliver near perfect accuracy, the CNN can be modified to improve on the misclassification. Furthermore, Model-1 does exhibit some overfitting seen in Fig. 1. Regularization can help with overfitting. Because of these risks, human evaluation could be considered for those instances where false positive or false negatives occur as a check against misclassification until the model delivers greater than 99% accuracy.

What further analysis needs to be done or what other associated problems need to be solved?

It is recommended that the CNN be expanded with more layers and include regularization with BatchNormalization. Layer expansion can provide more neurons to

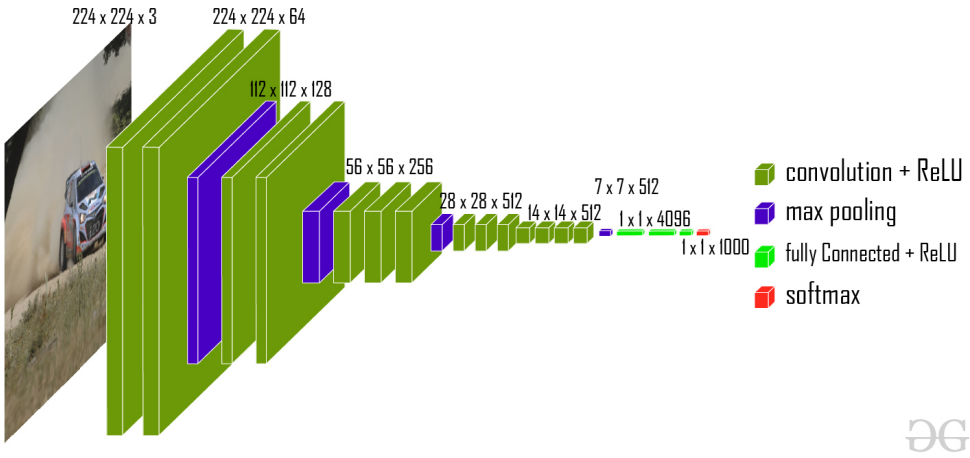


Figure 5: Specialized VGG16 neural network.

train on which could enable capture of additional features or patterns that could be missed with the smaller models. Applying image augmentation could also benefit learning and should be implemented. Image augmentation is provide more perspective on the images enabling better image classification. Combining models may also be beneficial. For instance, transfer learning with VGG16 and ResNet did not prove successful; however, combined with CNN, e.g., Model-1, could potentially improve model predictions and lower the occurrence of both false positives and false negatives.

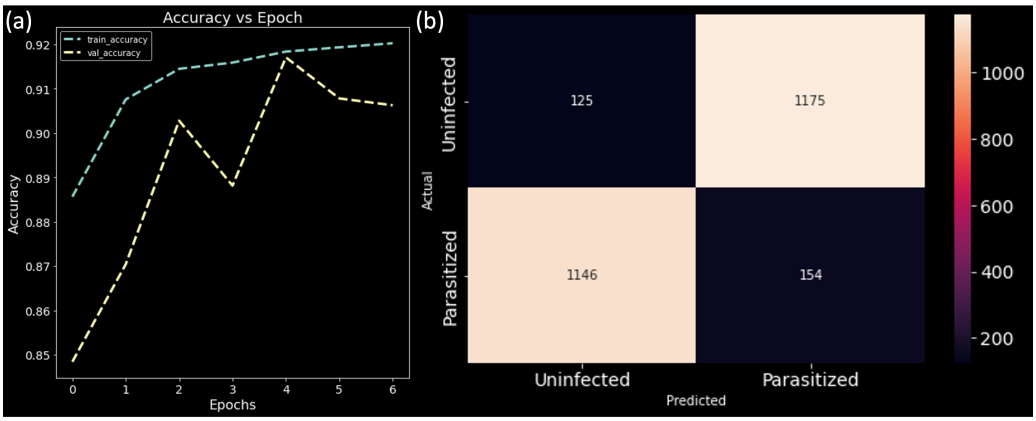


Figure 6: Model-5 (a) accuracy and (b) confusion matrix for the ResNet model (*not good*).