Modeling an optimal microscope hardware for an mhealth autonomous malaria detector

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Abstract

Mobile health with machine learning provide a good opportunity to help in the diagnosis of health conditions using microscopy without the need of an expert in remote placess. In this paper, I will explore a model that finds the optimal hardware settings for an mhealth microscope that will help in the diagnostic of the malaria. The theoretical analysis was done considering that mhealth devices must be build using affordable hardware.

1 Introduction

Light microscopy analysis is a very usefull medical method to diagnose many illnesses from cancer detection to conditions caused by other organisms such as tuberculosis, malaria and plasmodium. From the previous conditions, Malaria is a disease caused by a parasite that is transported by the mosquito and it is endemic in countries around the equator. Given that most of the malaria cases happen in developing countries, where resources are scarse, detection by light microscopy is the main method of illness detection. Another thing to consider is that the latest detection method requires special training, maintenance and sometimes support equipment which reduces the amount of qualified workers. Finally, the amount of doctors in developing counries tend to be lower and the specialist are located mostly in big cities where some of the illnesses are not recurrent.

Despite its low maintenance and high availability, light microscopy analysis requires a trained specialist to be effective. In countries such as Peru,56.9% of the patologists are located in Lima city, the capital, just like most of the medical specialists [1]. Also, malaria is more common in the rural areas of Peru or in the jungle where doctors are scarse and sometimes the only doctors that arrive there are the students doing their rural service with little to no equipment. Thus, the non specialized doctors may only use the symptom analysis as their only diagnostic tool. However, relying only in symptoms without any microscopy analysis can be dangerous for the patient and succeptible for errors. It also allows higher mortality, drug resistance and the complication of the illness if not treated correctly.

Given these restrictions, mhealth and machine lerning can provide tools and resources to the medical personnel in places where specialists and cutting edge hardware are scarce. In terms of hardware, smartphones can be adapted for the purpose by using compatible attachments that allows the device to capture microscopic images [2] The attachments can go from a 3D printed holder that will align the camera lens to an optical microscope, a custom CMOS microscope camera attachment to an smartphone to a total custom new hardware using affordable items such as a Raspberry Pi. Also, machine learning provides with the algorithms to perform image analysis and detection of infected cells. The purpose of this work is to find an appropiatehardware features for an mhealth solution by simulating the physical layer and the neural network that this system is going to use.

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2 Previous Works

There are many previous works related to mobile health and its challenges over the time. An early work was done in 2014 where the researchers attached a smartphone to a camera and detected diseases using a convolutional neural network. [6] Other studies focused on creating a portable microscope that sends the data to a laptop [8] or creating a microscope using a raspberry pi [7]. For the part of the neural network, there are publications related to the features of MobileNet from the developers [5, 3] and publications where the neural network was deployed successfully [4]. Finally, there are some works related to the hardware optimization using neural networks, these were useful in uderstanding more detailed models for modelling the physical system of a microscope capturing the data. [9]

3 The Dataset

The dataset for this research is going to be the malaria dataset from tensorflow. The data contains 27558 cropped pictures of blood cells from the thin blood smear slide. It contains a combination of healthy and infected blood cells half of the sample is infected and the rest are healthy. The data comes in the RGB format and it was normalized and resized to a 224x224 format so it can fit into the neural network.

4 System settings

The first thing to consider are the restrictions where the system is going to be deployed. For the hardware specs, the two things to be considered are the ilumination field for the microscope and the type of lens that the mhealth microscope is going to use. For the Neural Network, the main restriction to consider is that the internet connection can be little to non existent in rural areas. This restriction, makes our choice of convolutional neural networks restricted, fortunatelly, there are neural networks architectures that require less power and can be deployed inside a smartphone. The chosen neural network employed is MobileNetv2 and the system is represented in (Figure 1)

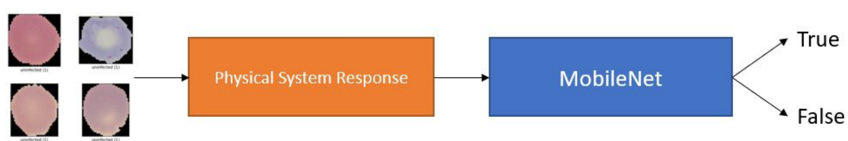

Figure 1: Malaria detection system

4.1 Physical Layer

For the physical layer, the light is going be modeled as a phase object that goes through an ilumination pattern. Then, it is filtered by the aperture of the lens that can be represented as a fourier mask. Once the physical layer is applied, the the data goes to the model where the classification is performed. For this research there will be two scenarios, one where the lens and the illumination pattern are optimized. The second one is where only the illumination pattern is optimized, the lens remains the same for all the channels. The reason for this decision is because mhealth devices tend to be used in many types of microscopes, thus an optimized microscope lens may make the theoretical device more expensive and less affordable for its purpose.

4.2 MobileNet

Given that the hypotetical machine learning application is not going to be run by a CNN hosted in the cloud, the computational limits, efficiency and size of the neural network has to be considered. These features are part of the design of MobileNets which scarifices part of the precission for a smaller size and speed [3]. In practice, this architecture proced to be successful in classification problems like the analysis of the citrus leaf desease, achieving an accuracy of 92% [4]. MobileNetv2, the latest update of the neural network architecture is available at tensorflow and it is lighter than the original version yet more efficient. It can outperform other state-of-art real time detectors on COCO dataset in terms of accuracy and complexity. [5]

5 Code

All the physical phenomena, from the light modelling as a phase object to the filtering was encapsulated into a custom component that runs the equations for every channel. The illumination pattern is a tensorflow variable that can be optimized and it is different for each color channel. The apperture panel remains the same for each channel. After performing all the equations, the final image is send to the neural network. The number of epochs needed to have a good optimization is hard to find. For instance, some researchers trained their models for malaria, plasmodium and tuberculosis detection with 500 epochs for each dataset. However, their model is simpler with only 2 convolutional layers, a pooling layer and a fully connected layer and they ran their experiments in 2016, before MobileNets [6]. For this experiment the amount of epochs is going to be between 50 and 75 because at that amount, accuracy on the validation dataset is over 90%.

6 Results

By running the algorithm multiple times, it is revealed that the full optimized model needs less epochs to have and maintain an accuracy over 90% compared to only optimizing the illumination field.

6.1 Full physical system optimized

In this section, all the elements of the physical layer are optimized, the effects of the physical layer can be seen in the following (Figure 2)

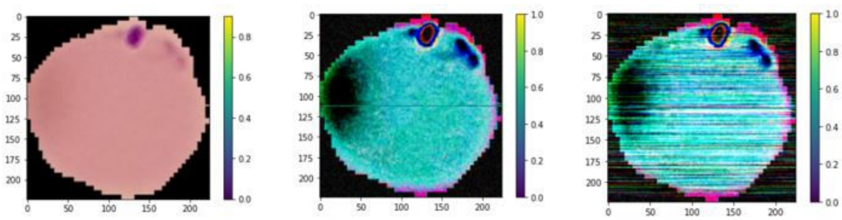

Figure 2: Left raw malaria infected cell, center, malaria cell from the default physical layer, right, cell after the optimized physical layer

A full optimization of the physical layer is fast compared to the optimization of the illumination pattern and it usually gets an accuracy over 90% in at least 40 epochs. After at least 75 trainings, the model achieved has a good AUC and precission-recall curve (Figure 3)

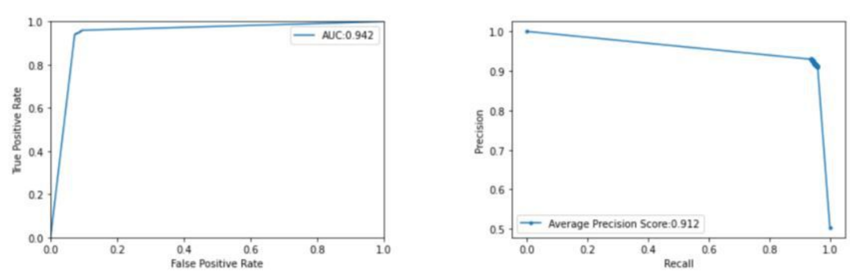

Figure 3: ROC curve of the system and Precision-recall curve

It also has the following confusion matrix (Table 1)

Having good values for the AUC and the precission recall curve means that the physical system works correctly and the image is not destroyed in the process. The most important thing in this project is to shown the learned physical layers. From this optimization, the optimal lens phase response is represented in Figure 4 and the optimal illumination phase pattern is in Figure 5. One particular thing of these optimized lenses are that most of the phase delay are on the edges of the lens. This could mean that the lens is trying to correct the border aberrations. Another possible cause is the type of

Table 1: Confusion Matrix for full optimized physical layer

	Predicted False	Predicted True
False	0.92	0.08
True	0.06	0.94

the image, the image in the dataset contain black backgrounds which has a significant impact in the frequency.

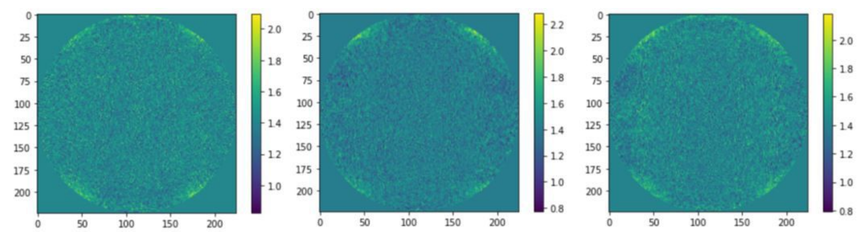

Figure 4: Optimal lens response for the red channel(left), green channel(center) ,blue channel(right)

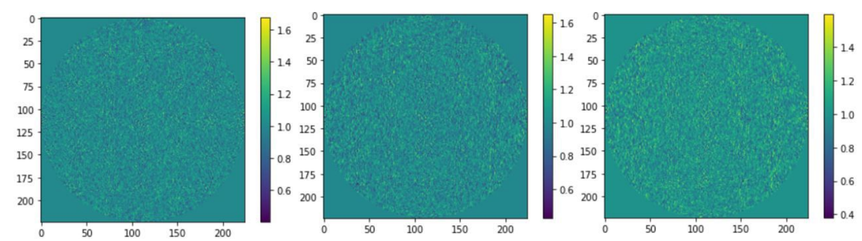

Figure 5: Optimal illumination phase response for the red channel(left), green channel(center) ,blue channel(right)

Given that the illumination pattern is generated by a 228x228 screen which is in practice expensive, the algorithm was ran again with a 28x28 matrix. In the physical world, this can represents a 28x28 LED array, something that is feasible and maintains the availability of a mhealth device. Its phase mask is upsampled in order to cover the image dimensions. There were no significant changes in the time that it took to optimize the illumination pattern. The final result, as expected is a less granular patern compared to the original 224x224 illumination mask that can be seen in Figure 6

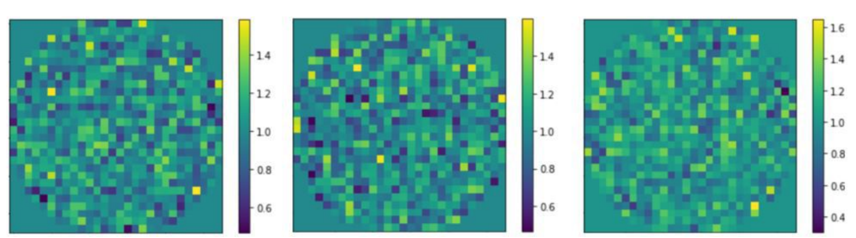

Figure 6: 28x28 optimized illumination phase response for the red channel(left), green channel(center) ,blue channel(right)

6.2 Illumination optimized only

As mentioned in the physical layer section, mhealth applications have to work with the available elements and creating a custom element may not be feasible. Thus, the only element that will be optimized will be the illumination pattern. Optimizing only the illumination pattern takes more time than a full optimization but it still provides good results.

Table 2: Confusion Matrix for only illumination optimization

	Predicted False	Predicted True
False	0.93	0.07
True	0.05	0.95

The follwing image describes the theoretical phase of the illumination phase patterns for the mhealth microscope 7 and with a good performance on a well trained neural network, it is possible to develop an mhealth microscope with an optimized illumination field.

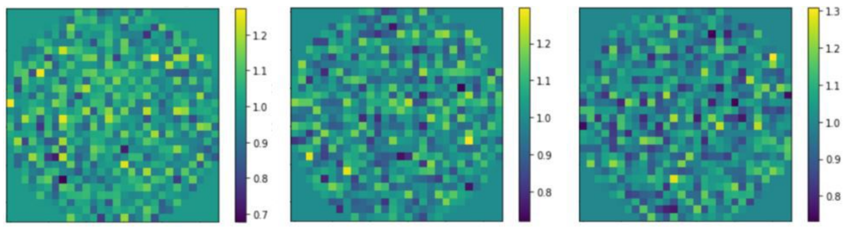

Figure 7: Ilumination optimized field for the red color(left), green(middle) and blue (right). This is for a non optimized lens

7 Discussion and Further Work

MHealth offers a great opportunity to improve the detection of illnesses in rural areas of developing countries, combined with artificial intelligence it may help nurses and non specialized doctors in doing microscopic analysis in places where communications with specialists are not possible. Many projects and implementations on mobile health considered custom illumination patterns. One projectdecided to create an entire low cost sub-micron resolution microscopy using open hardware without considering the smartphone camera as the light sensor because of the aberrations caused by the lens. [7]. The purpose of this research is to simlate the ideal components for an autonomus mhealth system and paired with a deep learning algorithm. Thus, in order to improve the system and the hardware in mhealth, it is important to model properly the aberrations caused by the smartphone lens. One solution for this problem is to use the inverse lens of the smartphone is to use a complex pupil function, another one is to use the smartphone lens in reverse manner which is cost effective. [8] This study began as a analysos to find the optimal hardware to focus on studying light patterns for every disease that can be diagnosed using the microscope. The main reason for adopting this position is because the illumination pattern is something that can be modified using an electronic circuit with a driver in the mhealth device. Further work on this topic would be studying different illumination patterns for other types of illnesses such as tuberculosis or other parasites and use a more accurate model.

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