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AUTOMATIC DETECTION OF MALARIA PARASITE FROM BLOOD IMAGES

A. Ms. Deepali Ghate[1] *(Information Technology, DCOER, Pune, India),*
B. Mrs. Chaya Jadhav[2]*(Information Technology, DYPIET,Pune, India),*
C. Dr. N Usha Rani[3] (HOD-ECE Department, Vignan's University, AP, India)

Abstract

Malaria is a serious disease for which the immediate diagnosis is required in order to control it. Microscopes are used to detect the disease and pathologists use the manual method due to which there is a lot of possibility of false detection being made about the disease. If the wrong detection is done then the disease can turn into more severe state. So the study about the computerized diagnosis is done in this paper, which will help in immediate detection of the disease to some extent, So that the proper treatment can be provided to the malaria patient. Also the image processing algorithm is used which will reliably detect the presence of malaria parasite from Plasmodium falciparum species in thin smears of Giemsa stained peripheral blood sample. Some image processing algorithms to automate the diagnosis of malaria on thin blood smears are developed, but the percentage of parasitaemia is often not as precise as manual count. One reason resulting in this error is ignoring the cells at the borders of images. This paper removes the human error while detecting the presence of malaria parasites in the blood sample by using image processing and automation. This is achieved by using Image Segmentation techniques to detect malaria parasites in images acquired from Giemsa stained peripheral blood samples. This is comparative study of two methods for detecting malaria parasites, first method is based on segmentation and second uses feature extraction using minimum distance classifiers. We built the malaria detection system in a robust manner so that it is unaffected by the exceptional conditions and achieved high percentages of sensitivity, specificity, positive prediction and negative prediction values.

Introduction

Malaria is a life-threatening parasitic disease, caused by the protozoan parasites of the genus Plasmodium and is transmitted through the bite of a female Anopheles mosquito. Inside the human body, the parasite undergoes a complex life cycle in which it grows and reproduces. During this process, the red blood cells (RBCs) are used as hosts and are destroyed afterwards. Hence, the ratio of parasite-infected cells to the total number of red blood cells called parasitaemia can be used as a measure of infection severity and is an important determinant in selecting the appropriate treatment and drug dose.

Malaria is a serious global disease and a leading cause of morbidity and mortality in tropical and sub-tropical countries. It affects between 350 and 500 million people and causes more than 1 million deaths every year. There were an estimated 190311 million clinical episodes of malaria, and 708,0001,003,000 deaths in 2008. It becomes the 5th cause of death from infectious diseases worldwide in low income countries. Yet, malaria is both preventable and curable. Rapid and accurate diagnosis which enables prompt treatment is an essential requirement to control the disease.

Currently, clinical diagnosis primarily utilises microscopy to study the prepared blood smears. However, evaluation of smears is arduous and time consuming, especially in situations where large numbers of samples require reliable analysis. Hence, it is important to develop an automated image analysis that is able to identify the uninfected and infected RBCs in a blood smear image.

Related Work

In the paper Estimating Malaria Parasitaemia from Blood Smear Images the author Silvia Halim , Timo R., BretSchneider, Yikun Li used pattern matching and template extraction. Malaria Parasite Detection in Peripheral Blood Images F. Boray Tek, Andrew G., Dempster used the method of Baysian Pixel classifier, k-nearest neighbor classifier. In Segmentation of Malaria Parasites in Peripheral Blood Smear Images Vishnu V., Makkapatti, Raghuveer M. Rao used image segmentation and chromatin dot selection. Malaria is caused by protozoan parasites of the genus Plasmodium. There are four species of Plasmodium that infect man and result in four kinds of malarial fever: P. falciparum, P. vivax, P.ovale, and P. malariae. P. vivax shows the widest distribution and is characterized by reappearances of symptoms after a latent period of up to five years. With the similar characteristics, P. ovale appears mainly in tropical Africa. P. falciparum is most common in tropical and subtropical areas. It causes the most dangerous and malignant form of malaria without relapses and contributes to the majority of deaths associated with the disease. P. malariae is also widely distributed but much less than P. vivax or P. falciparum.

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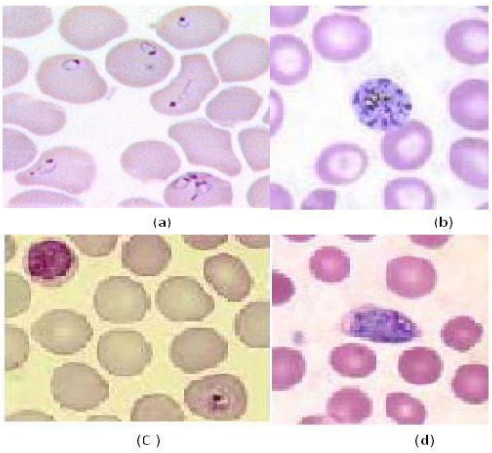
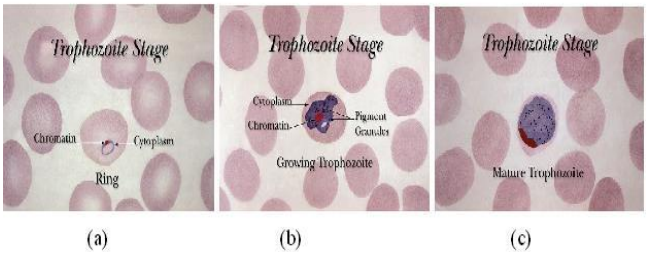


There are three phases of development in the life cycle of most species of plasmodia: exo-erythrocytic stages in the tissues, usually the liver; erythrocytic schizogony (i.e. protozoan asexual reproduction) in the erythrocytes; and the sexual process, beginning with the development of gametocytes in the host and continuing with the development in the mosquito.

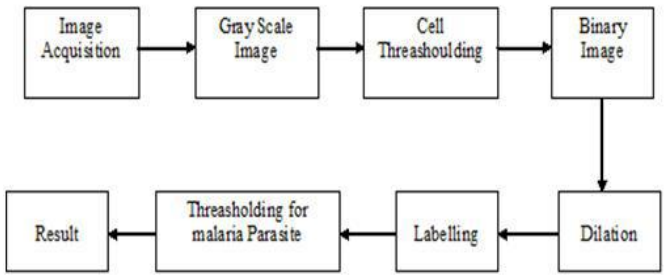
When an infected mosquito bites humans, several hundreds sporozoites (the protozoan cells that develop in the mosquitos salivary gland and infect new hosts) may be injected directly into the blood stream, where they remain for about 30 min and then disappear. Many are destroyed by the immune system cells, but some enter the cells in the liver. Here they multiply rapidly by a process referred to as exo-erythrocytic schizogony. When schizogony is completed, the cells produced by asexual reproduction in the liver termed merozoites are released and invade the erythrocytes. In Plasmodium vivax and P. ovale, some injected sporozoites may di_erentiate into stages termed hypnozoites which may remain dormant in the liver cells for some time before undergoing schizogony causing relapse of the disease. When the released merozoites enter erythrocytes, the erythrocytic cycle begins. This process is referred to as erythrocytic schizogony. Within an erythrocyte, the parasite is first seen microscopically as a minute speck of chromatin surrounded by scanty protoplasm. The plasmodium gradually becomes ring-shaped and is known as ring or immature trophozoite(Fig.a). It grows at the expense of the erythrocyte and assumes a form differing widely with the species but usually exhibiting active pseudopodia (i.e. projections of the nuclei). Pigment granules appear early in the growth phase and the parasite is known as a mature trophozoite (Fig.c). As the nucleus begins to divide, the parasite is known as a schizont (Fig.d-f). Dividing nucleus tends to take up peripheral positions and a small portion of cytoplasm gathers around each. The infected erythrocyte ruptures and releases a number of merozoites which attack new corpuscles and the cycle of erythrocytic schizogony is repeated. The infection about this time enters the phase in which parasites can be detected in blood smears. Some merozoites on entering red blood cells become sexual gametocytes, instead of asexual sch-izonts. When gametes are ingested by a mosquito, the cells rapidly undergo gamete production. This is the third phase of development in the life of plasmodium, the sexual process of reproduction in a mosquito.The figure for the development of plasmodium parasite is as follows.



System Architecture

Method-1

System architecture used for Malaria parasite detection involves following steps: Threasholding, gray scale image conversion, binary image, edge detection algorithm, thinning of binary image, labelling algorithm.



1 Image Acquisition

The input images of Giemsa stained blood smears are selected from the database Library. Images are of different shape and sizes. Images show high variations in intensity, contrast color tone, etc.

2 Image Preprocessing

The pre-processing block is designed, to remove unwanted effects from the image and to adjust the image as necessary for further processing The microscopic input image is converted from RGB to gray scale to reduce the processing time. RGB to gray conversion is done by averaging all the three components i.e. R, G and B which results in gray scale.

3 Image Smoothing

Smoothing is often used to reduce noise within an image or to produce a less pixelated image.

Most smoothing methods are based on low pass filters. Smoothing is also usually based on a single value representing the image, such as the average value of the image or the middle (median) value. The simplest approach is neighborhood averaging, where each pixel is replaced the average of the by value pixels contained in some neighborhood about it. The simplest case is probably to consider the group of pixels centered on the given pixel, and to replace the central pixel value by the un-weighted average of these (nine, in case of 3*3 neighborhood) pixels.

4 Thresholding

Thresholding is the simplest method of image segmentation. From a grayscale image, thresholding can be used to create binary images.

Image Segmentation

1) The purpose of image segmentation is to partition an image into meaningful regions with respect to a particular application.

2) The segmentation is based on measurements taken from the image and might be Gray-level, colour, texture, depth or motion.

5 Dilation

Dilation is one of the two basic operators in the area of mathematical morphology, the other being erosion. It is typically applied to binary images, but there are versions that work on grayscale images. The basic effect of the operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels. Thus areas of foreground pixels grow in size while holes within those regions become smaller.

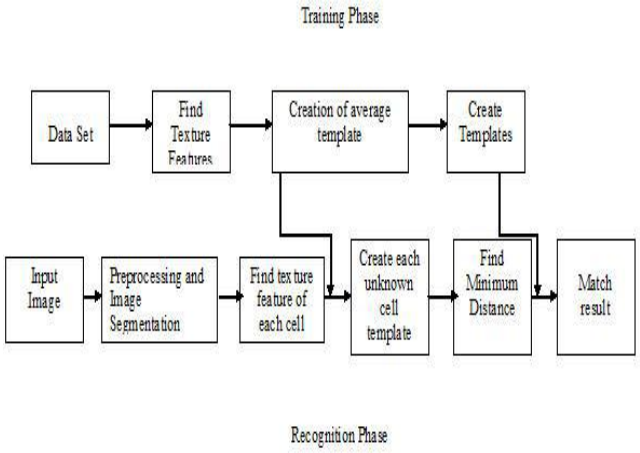
Method-2

There are two phases in this architectural model:

1. Training Phase and 2. Recognition Phase

3.2.1 Training Phase: In this phase we find out texture features from the data set and create average template, which will mapped with each cell template in recognition phase.

3.2.2 Recognition phase: This is second phase in this module, in which we find texture feature of input image and create template. Compare result with average template from training phase and find the minimum distance and display the final result.



Result Analysis

In order to test and compare the performance of the two methods which we have used in our system design can be explained with the help of some parameters such as, Accuracy, Sensitivity and PPV (Positive Predictive Value). Formulae for the same are given below,

Accuracy= (TP+TN) / (TP+TN+FP+FN)
Sensitivity= (TP) / (TP+FN) PPV= (TP) / (TP+FP)

Where, TP: True positive, TN: True negative, FP: False positive, FN: False negative.

Confusion Matrix for Model I

		Yes	**No**	
Model-I	Yes	35	5	Positive predicate value: 87.50%
	No	8	32	Negative predicate value: 80.00%
		Sensitivity: 81.39%	**Specificity: 86.49%**	**Accuracy: 83.75%**

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Confusion Matrix for Model II

		Yes	No	
Model-II	Yes	31	9	Positive predicate value: 77.50%
	No	12	28	Negative predicate value: 70.00%
		Sensitivity: 72.93%	**Specificity: 75.76%**	**Accuracy: 73.75%**

Conclusion

The detection of Malaria parasites is done by pathologists manually using microscopes. So, the chances of false detection due to human error are high, which in turn can result into fatal condition. This paper curbs the human error while detecting the presence of malaria parasites in the blood sample by using image segmentation and feature extraction using minimum distance classifier. It shows the comparative study between two methods as mentioned above. In image segmentation we are getting the accurate and required results in the short period of time whereas in case of feature extraction more time is required i.e more CPU utilization is there.. The system in a robust manner so that it is unaffected by the exceptional conditions and achieved high percentages of sensitivity, specificity, positive prediction and negative prediction values. And the extraction of red blood cells achieves a reliable performance and the actual classification of infected cells.

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