Survey on Malaria Detection using Machine Learning Classifiers

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***Abstract*—Malaria is a serious and sometimes fatal disease caused by a parasite that commonly infects a certain type of mosquito which feeds on humans. People who get malaria are typically very sick with high fevers, shaking chills, and flu-like illness. Although malaria can be a deadly disease, illness and death from malaria can usually be prevented. This disease arises due to damaging of red blood cells in blood and identifying of which is a difficult proposition in a clinical set-up. Many automated methods have been found to predict or diagnosing the malaria disease. This paper presents a survey on various automated systems for predicting or detecting malaria disease using different techniques like machine learning and Image Processing. In our observation, we found that machine learning techniques have wider applicability for critical diagnosis of malaria which in turn helps the clinicians for diagnosing the disease.**
Keywords: Malaria, Red blood cells, Machine learning, Image processing.

I. Introduction

Malaria is a mosquito-borne parasitic infection spread by a female Anopheles mosquito infected by the Plasmodium parasite. It is a single-celled parasite that multiplies amongst the red blood cells of humans as well as in the mosquito's intestine. When the female mosquito feeds on an infected person, the parasites are ingested along with the human blood. The parasites multiply in the mosquito's gut and these infectious forms are passed onto another human when the mosquito feeds again. You can get malaria: If you have been bitten by an infected female Anopheles mosquito If you receive infected blood from a malaria patient during a blood transfusion Malaria can also be transmitted from an infected mother to the child during pregnancy through the placenta, or be transferred to the baby through blood during childbirth, resulting in 'congenital malaria' (malaria which has been passed from mother to infant).

There are 4 species of the Plasmodium parasite that can infect the female Anopheles mosquito and cause malaria in humans – P. falciparum, P. vivax, P. ovale and P. malaria. Of these, Plasmodium falciparum is the most dangerous; a malarial infection caused by this parasite can kill rapidly. The parasites, P. vivax and P. ovale can lie dormant in the liver for up to a year before causing any symptoms. They can even remain dormant in the liver again and cause relapses late.

There are various techniques to diagnose malaria, of which manual microscopy is considered to be "the gold standard". However due to the number of steps required in manual assessment, this diagnostic method is time consuming (leading to late diagnosis) and prone to human error (leading to erroneous diagnosis), even in experienced hands. As mentioned, this manual approach of diagnosis is time consuming and may lead to inconsistency[1]. Microscopy method is "Gold Standard" for detecting malaria parasites and estimating parasite density [2].There are two types of blood films prepared for microscopic diagnosis: thin and thick [2]. A thin blood smear is used to identify species of the parasite, as the appearance of the parasite is retained. A thick blood smear is used to detect the presence of parasite and parasite density[2].

In this survey ,we focused on various automated methods used to detecting malaria using machine learning classifiers like ANN(Artificial Neural Network)[1], SVM (Support Vector Machine)[2] and CNN(Convolutional Neural Network)[4].

II. RELATED WORK

A. Image Preprocessing

Basically, there are three main objectives for image preprocessing. One is to resize the image for the purposes of either magnifying the image through digital zooming, or reducing the image size in order to speed up processing. The second objective of image pre-processing is to reduce or eliminate noise from the acquired image. The third objective is to enhance the image contrast for visual evaluation.

Ahmedelmubarak Bashir et al.[1] used different image enhancement methods to improve the quality of images and remove noise. All images are rescaled to have the same size using the built in MATLABTM function imresize. Both captured images and CDC images are converted from RGB to gray scale to reduce the processing time. RGB to gray conversion is done by using the built in MATLABTM function rgb2gray. Filtering operation using a square median filter is performed to images. This operation served to remove spurious noise present in the images.

Ishan R. Dave [2] was made to reduce variations due to various factors like lighting conditions and concentration of staining solution. The captured images are converted in HSV colorspace to reduce variations due to brightness and concentration of stain solution, which highly affects in RGB colorspace.

Courosh Mehanian et al.[4] used White balancing techniques to compensate for the color variation. Traditional white balancing involves the scaling of red, green, and blue (RGB) pixel valuesbased on the mean color of the brightest pixels in each image individually, which can result in color distortion and exaggerated intra-slide color differences. This white balancing technique pools the pixels from all FoVs and computes a global color balance affine transform for each blood sample.

B. Image Segmentation

Image segmentation is the fundamental step to analyze images and extract data. Image segmentation is a mid-level processing technique used to analyze images and can be defined as a processing technique used to classify or cluster an image into several disjoint parts by grouping the pixels to form a region of homogeneity based on the pixel characteristics like gray level, color, texture, intensity and other features [5], [6]. The purpose of the segmentation process is to get more information about the regions of interest in an image, which helps in annotation of the object scene.

Ahmedelmubarak Bashir et al.[1] clearly differentiate between the object and the background in an image. There are two objectives for image segmentation. One is to isolate the red blood cells (RBCs) from the background and the second is to extract all the RBCs and process them individually in order to facilitate the process of feature extraction.

In [2] ,the image is segmented into foreground (stained particles i.e. parasites of all life stages, leukocytes, platelets and many other artifacts) and background (non-stained particles i.e. liaised red blood cells). the segmentation is done using adaptive histogram thresholding technique to segment stained particles from the saturation channel. Mathematical morphological operations are used to extract the desired components from the segmented binary image. Holes are filled in order to eliminate small background areas inside the foreground contours.

Suman Kunwar et al.[3] subdivides an image into its constituent regions or objects. The level of detail to which the subdivision is carried depends on the problem being solved. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. They used two types of segmentation have to be implemented to get the result. Watershed segmentation and Color-based segmentation are used in the research.

Courosh Mehanian et al.[4] uses segmentation on multiple color spaces based on a greedy hierarchical grouping of graphs. This leads 10K detections per image, which would drastically slow down our framework. Processing flow in R-CNN (and its variants Fast R-CNN [7] and Faster RCNN [8]) consists of region proposals, followed by classification, followed by post-processing to refine the bounding boxes and eliminate duplicate detections.

C. Feature Extraction

In [1],we need to extract features from the image array and compute new variables that concentrate information to separate classes. The set of features should discriminate between infected and non-infected RBCs as well as possible. An additional requirement is robustness, so that the results can be reproduced for new independently collected material. the feature extraction process can be expressed in terms of the definition of the zone of measurement, and then measure the information required from that zone. Intensity features are based only on the absolute value of the intensity measurements of the image.A suitable threshold is defined as clutch that can distinguish between the infected and non-infected RBCs.

In [2],Regions of interest are cropped from the original image according to size and location of labels. Each ROI is square with centroid at centroid of the label. Different kinds of features based on shape, texture and color are extracted from the ROIs. Area feature is obtained from frequency domain after passing gray scale ROI to a high pass filter (gaussian, standard deviation =1), followed by global threshold to get binary image. Some stained objects (non-parasite) of low frequency components are removed successfully using this feature.

In [3], Feature extraction uses two phases in architectural model: 1) Training Phase and 2) Recognition Phase which helps to recognize the MP.

In [4],We extract features on those candidate objects that survive the distractor filter. The recent widespread adoption of CNNs for feature extraction and classification has led to notable breakthroughs in performance for various computer vision tasks [9-12]. We employ CNNs using the Caffe Deep Learning Framework [13]. VGG is used as a feature extractor, the output of 2nd fully connected layer (after dropout) is used as the feature vector.

D. Classification

1) ANN(Artificial Neural Network: The NPRTOOL command was used to generate a MATLABTM script which solves a Pattern Recognition problem with a Neural Network and it uses back propagation algorithm. In the script, firstly the input and target data was defined. The input dataset is a 7403 matrix, which represents the selected features. The target data is a 2740 matrix, which contains zeros and ones only with respect to normal and abnormal features in the input matrix. The hidden layers was set to 20, and then network training was performed using 740 erythrocytes. The network was tested using the rest of erythrocytes in addition to 244 erythrocytes randomly chosen from different images and its performance was evaluated[1].

2) SVM(Support Vector Machine: Cubic support vector machine (SVM) classifier is used for classification. The classifier is trained using all 123 features of 2323 ROIs (extracted from

43 training data images) and tested on 2290 ROIs (extracted from 44 testing data images). There is no overlap between training dataset and testing dataset[2].

3) CNN(Convolutional Neural Network: One approach is to use the CNN as both feature extractor and classifier. Another option is to use the CNN as feature extractor and a different algorithm as external classifier. The first choice has some advantages, including simplicity, speed, and the fact that the CNN is trained with a large (augmented) number of thumbnails. The second option provides more flexibility in responding to new distractor types or sample preparations discovered in the field[4]. Transfer learning [14-16] assures us that a universal CNN feature extractor, trained on a broad set of samples available in-house, can provide discriminative features in most field settings, while an external classifier can be fine-tuned to local conditions. Initially, the CNN and external classifier are trained on the same in-house samples. We use logistic regression [17] as the external classifier for two reasons. First, logistic regression mimics the CNN's fully fully-connected + SoftMax output. Second, the software package [18] implements a robust, large-scale learning algorithm for logistic regression based on stochastic gradient descent.

III. CONCLUSION

Classification accuracy may vary with image quality, quantity , different feature combinations and also with classifier used.In this survey we discuss SVM,ANN and CNN classifier for detecting malaria.The SVM gives better accuracy in detecting the presence of Plasmodium parasites.but when compared to the neural network, which has been trained with the back propagation algorithm, improves the accuracy and performance of the system.An ANN also gives better accuracy but it is less than SVM classifier. CNN-based malaria detection algorithm, that applies CNN models with sufficient training and validation data and patient-level accuracy to meet two key use-cases of the automated malaria problem.In this survey we proposed that Deep learning with CNN gives high accuracy than other classifiers .

It is worth to note that, accuracy may be improved by using more images for training, by improving slide quality and improving image acquisition method. This work can be extended for detecting different Plasmodium species and their different life stages.

We have presented an approach and developed an algorithm for detecting malaria, automated malaria detection and quantification of malaria infection. Also, we developed a strategy to train with machine learning,adaptabletodetectionof malaria with other types of parasite and also discussto increase the predictive value with results.

In future, classification models can be tested with different image quality, quantity and features to achieve better classification accuracy. Large feature dimension is a reason for low classification accuracy. Therefore, the feature combinations that give better performance should be chosen. Similarly, use of multilevel or hybrid classifier will also help in improving the classification accuracy.

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